Hacettepe University Graduate School of Social Sciences

Department of Economics

EXTREME RISK CONNECTEDNESS OF SOVEREIGN CREDIT DEFAULT SWAPS: EVIDENCE FROM BRICS AND MIST COUNTRIES

Ebru YENİCE

Ph. D. Dissertation

Ankara, 2023

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ABSTRACT

YENİCE, Ebru, Extreme Risk Connectedness of Sovereign Credit Default Swaps: Evidence from BRICS and MIST Countries

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To analyze the extreme risk spillover effect, this thesis proposes dynamic EVT-VaR extended joint connectedness framework based on extreme value theory. The spillovers among sovereign CDS of BRICS and MIST countries using the data from March 18, 2011 to June 1, 2022 were examined. Global financial factors were included in the model and their effects were analyzed. Besides, using the Principal Component Analysis (PCA), an extreme connectedness analysis was carried out for sovereign CDSs of many leading economies around the world. Moreover, the dynamic EVT-VaR extended joint connectedness framework and the quantile extended joint connectedness approach were compared using sovereign CDSs of BRICS and MIST countries.

It has been found that there is a strong connectedness among the sovereign CDSs of the countries in the BRICS and MIST, and the spillover effect has fluctuated over time due to extreme events. Among these countries, Russia has a pronounced role as a net transmitter of shock. After Russia, Mexico has also been one of the important drivers in explaining the variability in the sovereign CDS spreads in BRICS and MIST countries, especially in 2017-2018 and after 2020.

Global financial markets have a limited impact on sovereign CDSs in the BRICS and MIST countries. Using the PCA analysis, we found that there is an unprecedented increase for the analysis period in the total connectedness of sovereign CDSs around the world after the Covid 19 pandemic and it continues to remain high at the present time. Finally, the quantile extended joint connectedness approach does not respond as sensitively as the dynamic EVT-VaR extended joint connectedness framework to extreme events that have occurred over time.

Another finding of the study is that Türkiye is not strongly interconnected with other economies. As a result of limited interconnectedness, Türkiye have been affected by systematic risks less. On the other hand, Türkiye has a high and volatile sovereign CDS

values, which means that the country's high-risk perception stems from events occurring within the country itself, rather than external factors.

Keywords

Extreme Value Theorem, Spillover Effect, Extended Joint Spillover Approach, Sovereign CDS, Extreme Risk Spillover

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LIST OF ACRONYMS AND ABBREVIATIONS

AIC	: Akaike's Information Criterion
AR	: Autoregressive
ARCH	: Autoregressive Conditional Heteroskedasticity
BMM	: Block Maxima Method
BRICS	: Brazil, Russia, India, China, South Africa
CDS	: Credit Default Swap
C-EVT	: Conditional Extreme Value Theorem
CISS	: Composite Indicator of Systemic Stress
CoVaR	: Conditional Value-at-Risk
DY	: Diebold and Yılmaz
ES	: Expected Shortfall
ES50	: Euro Stoxx 50
EU	: European Union
EVT	: Extreme Value Theorem
FED	: Federal Reserve System
FPE	: Final Prediction Error
FTSE	: Financial Times Stock Exchange
G7	: The international Group of Seven
GARCH	: Generalized Autoregressive Conditional Heteroskedasticity
GAS	: Generalized Autoregressive Score
GCC	: Gulf Cooperation Council
GEV	: Generalized Extreme Value
GFC	: Global Financial Crisis
GFEVD	: Generalized Forecast Error Variances Decompositions
GIRF	: Generalized Impulse Response Function
GPD	: Generalized Pareto Distribution
HS50	: Hang Seng [China] 50
IDD	: Independent and Identically Distributed
ICRG	: International Country Risk Guide
IMF	: International Monetary Fund
ISDA	: International Swaps and Derivatives Association
JSE	: Johannesburg Stock Exchange
KPSS	: Kwiatkowski–Phillips–Schmidt–Shin
MIST	: Mexico, Indonesia, South Korea, Türkiye
MLE	: Maximum Likelihood Estimator
MMVaR	: Mark to Market Value at Risk
OLS	: Ordinary Least Squares regression
OTC	: Over The Counter
PCA	: Principal Component Analysis
POT	: Peak over Threshold

Q-Q	: Quantile-Quantile
RV-EVT	: Realized Volatility EVT
SCDS	: Sovereign Credit Default Swaps
SENSEX	: Bombay Stock Exchange Sensitive Price Index
SMI	: Swiss Market Index
S&P	: Standard and Poor’s
TCI	: Total Connectedness Index
TVP	: Time Varying Connectedness
VaR	: Value at Risk
VAR	: Vector Autoregression
Var-Cov	: Variance-Covariance
VIX	: Chicago Board Options Exchange's Volatility Index
VSTOXX	: Euro Stoxx 50 Volatility EUR Price Index

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INTRODUCTION

The 2007-2008 global financial crisis shows that negative developments in one market affect other markets very quickly, such that negative market conditions turn into a systemic crisis. The rapid increase in the crises experienced in global markets necessitates acceleration of studies on methods for monitoring and managing market risks. This study focuses on the analysis of extreme risks and their transmission. Although extreme risks do not occur very often, a very large systemic crisis is triggered when they arise. For this reason, the need to develop techniques to measure extreme risks and to be able to make predictions are emerging in recent years.

Extreme risks are those that are unlikely to occur, but, if they occur, they lead to very large losses. The data related to extreme risks are limited due to the rare nature of extreme events. Therefore, it is relatively difficult to predict these infrequent events. However, efforts to estimate and hedge extreme risks in financial markets have gained importance recently because of their infectious characteristics.

With financial integration, it is seen that the spillover effects of different financial assets within a single country and among various countries have increased significantly. Studies show that spillover effects are very common during crises and the negative effects of crises spread very quickly. Therefore, if extreme events occur in a market or a country, the consequences of these devastating events spread in waves around the world quickly.

Determination of extreme risks is important for both investors and regulators. Since extreme risks have the potential to spread quickly, regulators need to estimate and take measures to deal with systemic risk. Estimation of extreme risks is also crucial to determine capital requirements in banking sector.

In this thesis, the Value at Risk (VaR) values obtained via the dynamic EVT method to measure the extreme risks of SCDS. Several studies have shown in the literature that the EVT method performs better than other conventional VaR estimation methods.

The focus of the thesis is measuring extreme risk volatility of sovereign credit default swaps (SCDS). The dynamic-EVT method is a semi-nonparametric method based on the Peak Over Threshold Approach. We perform out-of-sample risk estimation by fitting the Generalized Pareto Distribution (GPD) to the tail of the empirical distribution.

Studies focusing on the spread of the risk both among sectors and countries have become widespread in recent years. Using these research studies, policy makers and investors can take precautions by determining the influential countries and sectors where the systemic risk is most prevalent. Studies show that connectivity begins to upsurge even before the major crises. For this reason, spillover analyses are seen as an early warning mechanism for a possible financial crisis since they demonstrate the periods that are prone to crises.

In this thesis, extreme risk connectedness of SCDS has been estimated. Extreme risks of the sovereign CDSs of BRICS and MIST countries have been measured with the dynamic-EVT method via time-varying VaR values. Then, the connectedness of extreme risks has been examined using the risk metrics acquired from the EVT-VaR application.

This thesis contributes to the existing tail risk measurement literature by extending connectedness analysis to measure tail networks and by proposing a two-stage hybrid multivariate model for measuring extreme risk spillover. In the first stage, the dynamic EVT-VaR series was obtained by performing the univariate EVT analysis for each country's data. Then, the connectedness analysis was performed for the obtained risk metric series. Empirical studies show that the extreme risk spillover magnitude is significantly higher than that of the return and volatility spillovers. Therefore, studies that do not consider the extreme risk spillover are likely to underestimate the existing risk. Therefore, models which measure extreme risk spillovers have recently gained importance.

Although, there are extensive amount of studies using the connectedness analysis, applications on CDS are limited. To analyze the extreme risk spillover effect, this thesis proposes the dynamic EVT-VaR extended joint connectedness framework based on

Extreme Value Theory and the spillovers between sovereign CDS of BRICS and MIST countries using the data from March 18, 2011, to June 1,2022.

In this study, BRICS and MIST countries were chosen as the focus of the analysis of spillovers among sovereign credit swaps. In their study covering 38 countries, Bostanci and Yilmaz (2020) found emerging countries as the main driving force for global sovereign risk spillovers. While Turkey and Russia are the countries that mostly affect other countries in the measurement of connectedness, South Africa, Brazil, and Mexico follow these countries. As can be seen, the BRICS and MIST countries, which are the center of the credit risk network, form the basis of this study. The interaction of BRICS and MIST countries with other country groups is also addressed through the Principal Component Analysis (PCA).

CHAPTER 1

THEORY AND LITERATURE REVIEW

1.1CREDIT DEFAULT SWAP (CDS)

1.1.1 Introduction

Credit Default Swap (CDS) is an agreement that the investor is protected against credit risk in an exchange for a premium. The parties in a CDS contract are reference entity, protection buyer, and protection seller. Reference entity refers to the issuer of debt obligation that is subject to the contract. Reference entity can be a corporation or a sovereign government. The subject of this thesis is the sovereign CDS, which is issued for the sovereign government debt.

The CDS contract is made between the protection buyer and the protection seller. If the bond issued by the reference entity is not paid, the protection buyer demands a certain percentage of these bonds' value from the seller. Thus, the protection buyer transfers the risk of non-repayment of the loan to the third parties. The protection buyer pays the "premium" to the seller at regular intervals in exchange for this protection. The protection seller will provide "contingency payment" in the event of the bankruptcy of the reference entity. This payment is called as "contingency payment" since it is conditional on certain "credit events". The protection seller does not make any payment if there are no credit events at the end of the CDS term.

It should also be noted that although investors are protected against the credit risk by CDS contracts, other risks such as exchange rate and interest rate risks continue to be kept by investors. CDSs are not traded in central exchange markets because they are over the counter (OTC) contracts. The International Swaps and Derivatives Association (ISDA) has standardized the CDS contracts.

The ISDA has also defined credit events that trigger CDS contingent payments. Accordingly, the main credit events are listed in the 2003 ISDA Credit Derivatives Definitions (ISDA, 2013). The occurrence of any one of the credit events related to a credit derivative transaction triggers CDS payments. CDS events are bankruptcy, failure to pay, debt restructuring, obligation acceleration/obligation default, and repudiation/moratorium.

1.1.2 The Purpose of Using CDS Contracts

The primary purpose of CDS contracts is to "transfer the default risk" to third parties. The owners of the underlying debt protect themselves against the possibility of a default or similar credit events. CDS contracts are therefore used to hedge credit risks. These contracts are also extensively used for "proxy hedging", in other words, they are used to hedge the risk of other assets when direct hedging is not available, and the value of these assets are correlated with the CDS spread (IMF, 2013).

CDS contracts can also be used for "speculation". In the CDS trade conducted for the purpose of speculation, the investor does not hold the underlying debt. Speculation in CDS contracts lies in positive or negative beliefs about the default risk of reference assets. Investors shall bet on the default risk and declare their expectation about the credit risk of the debt. Specifically, in the case of SCDS, it is generally supposed that the speculation trading leads to a very rapid increase in the SCDS prices. Therefore, speculation trading leads to an upsurge in the country's risk. The measures forbidding speculation trading and the economic effects of this ban will be discussed in the following sections.

CDSs are also used for "basic trading" purposes. Here, profit is obtained by taking advantage of price differences between CDS and the underlying debt. For example, suppose that a country with a high risk of bankruptcy has issued treasury bonds. When determining the price of that bond, credit risk will be taken into consideration and the risk premium of the bond will be high. When the treasury bond is secured with a CDS contract, there should be an equivalence between the yield of the treasury bond with CDS protection and the low-risk countries' treasury bond. In other words, the price of the CDS should be determined by underlying asset returns. Otherwise, it is possible to obtain arbitrage profit by taking advantage of the price differences between the CDS and the underlying debt.

Lastly, CDS contracts can be used for "portfolio diversification" strategies considering their correlations with other assets. CDS trading provides new hedging opportunities for portfolio diversification. For example, CDS will be highly correlated with the price of underlying asset. However, the rate of return of this portfolio in this case will be equal to the riskless asset's return (Levy and Post, 2005).

1.1.3 The Determinants and CDS Spread and The Effects of CDS Initiation

The primary factors in determining CDS spread are the expected value of the payments of the protection buyer, the default probability of the underlying debt, and the recovery rate. In the price discovery process, it is widely discussed in the literature whether the bond market leads to the CDS market or not. Hassan (2015) found that sovereign CDS market is a source of price discovery to a large extent in adapting to new information. Also, in this study, Hassan (2015) found co-integration between CDS and bond spreads and concluded that there is a positive relationship between financial co-integration and price discovery of CDS in emerging economies, suggesting that with financial integration, the effects of global factors became more influential on the pricing of credit risks.

The determinants of CDS spread have long been discussed. In their study for China, Eyssell et al. (2013) reported that domestic economic factors were more effective than global factors in determination of CDS spread levels and changes in earlier years, whereas global factors were more relevant in explaining CDS spread especially during the global financial crisis. This result can stem from the integration of China with the international markets and the increase in the spillover effects among countries during the crisis periods. In addition, in line with the general findings in the literature, CDS spread leads to stock returns, thus confirming the leadership role of CDS spreads in price discovery.

In the case of sovereign CDS, default events appear to occur very rarely, even in high-risk countries. Therefore, CDS trading with the motive of speculation is increasing since the investor can earn a premium without fear of a default event. In this case, even if the country's default probability does not change, CDS spreads are affected by trade imbalances in both buy-side and sell-side. Therefore, liquidity has a significant impact on CDS pricing. To find the effect of different factors in CDS pricing, Badaoui et al. (2013) decomposed sovereign CDS and sovereign bond spreads into bankruptcy, liquidity, systematic liquidity, and correlation components. They found that sovereign CDS spread level and changes have been driven by liquidity incentive rather than bond spreads. Furthermore, the rise in CDS spreads during crisis periods is not due to an increase in the risk of bankruptcy but mainly because of the decline in the liquidity.

It is crucial to follow extreme CDS risks for policymakers and investors. Although there were many studies examining the effect of liquidity risk on CDS spreads, Irresberger et al. (2018) studied the effect of CDS liquidity tail risks on CDS pricing for financial and non-financial companies. They found that CDS liquidity tail risk led to a significant increase in CDS spread. The time-varying liquidity tail risk spikes in times of crisis, which increases the cost of hedging especially when the investor needs the protection the most. Studies show that both liquidity and tail liquidity risks are determinant in CDS spread pricing.

Systemic risks increase in the CDS market in crisis periods due to the increased dependencies among the contracts in CDS markets. Protection seller is exposed to a systemic risk, and they demand higher premium in return for this risk. Then, the CDS spreads soar up in the financial turmoil periods.

The effects of CDS initiation on the bond market have been discussed in many studies. CDS initiation improves the information transparency and helps to create new hedging opportunities for the investor. Shim and Zhu (2014) analyzed the effect of the CDS initiation on the corporate bond market in Asia. CDS trading lowered the cost of issuing new bonds and increased the liquidity of the bonds. These positive effects of CDS initiation are particularly striking for small firms and non-financial firms. However, these positive effects are reversed in times of crisis and bond spreads are higher in companies included in the CDS indices in this period.

The impacts of CDS initiation vary for commercial and sovereign bonds. The effects of CDS initiation on the sovereign bond market were examined by Ismeilescu and Phillips (2015). With CDS trading initiation, sovereign bond yields and borrowing costs reduce because of the improvement in price efficiency. Especially in high-risk countries where asymmetric information is widespread, the effects of this efficiency gain are more prominent. In high-risk countries, CDS trading initiation encourages the investor participation and increases the liquidity of underlying debt.

1.1.4 The Sovereign Credit Default Swaps

Sovereign CDS transaction volume has increased considerably in recent years. Sovereign CDSs provide valuable information on a country's default risk. We observe that SDCS spreads have increased significantly in the times of crisis.

2008-2009 Financial crises had a very devastating impact on the economy. When the systemic risks that are effective on the whole economy increase, crises have a profound effect. As the financial markets become more dependent on each other, the deterioration in one market spreads rapidly to other markets. Hence, it is important to measure and manage the dependency of the markets reliably.

Sovereign CDSs are also gaining importance in monitoring the state of the risk perception of a country. Sovereign CDS responds faster to additional information and news than other bond spreads, especially in times of crisis in emerging market economies (IMF, 2013). Sovereign CDSs act as a market indicator of a country’s default risk. Since sovereign CDSs are gaining importance in recent years so their usage to hedge default risks is increasing. Therefore, sovereign CDSs are a leading indicator of significant fluctuations and a tool in the assessment of the robustness of the financial sustainability of an economy.

According to EU Regulations, naked SCDS is prohibited, that is SCDS holders must have an underlying debt, and therefore should be exposed to the default risk. It was aimed to prevent sovereign CDS trading for speculation purposes. The main reasons for this prohibition are that SCDS are very sensitive to breaking news and have a probability of creating a systemic risk. On the other hand, since sovereign CDSs account for only 6% of the total global sovereign bonds, it is suggested that CDSs will not have a substantial impact on the bond yields (Ismeilescu and Phillips, 2015).

There are several studies related to the effects of the regulation on limiting SCDS trading. Salomao (2017) found that SCDS reduces the cost of bond issuing of a country and lowers the default probability for sovereign bonds. Therefore, 2012 CDS ban is welfare reducing at the current level of CDS to debt ratio (%5-%10) for European countries. However, after a certain threshold (50%-60%), the introduction of the CDS reduces the welfare of the country.

There is also very close relationship between political stability and CDS spreads. Political stability is generally affected by the possibility of the ruling party to be re-elected. Especially in emerging countries, it is observed that sovereign spreads, an indicator of the country's default risk, increase during the periods of political instability.

Government stability is measured through the sub-index within the International Country Risk Guide (ICRG). Comparative ratings of countries are calculated within the framework of political stability. In the study conducted by Scholl (2017) using ICRG, concluded that in general before the debt crisis, existing governments have increased their external debts to extend their mandate. Therefore, the political turnover is closely related with the high external debt and the probability of bankruptcy.

Since there is a close relationship between the possibility of political turnover and the risk of bankruptcy, institutional arrangements are made to limit the expenditures of governments. For this purpose, “fiscal rules” aiming to ensure fiscal discipline are put into effect. It is seen that especially sovereign spreads are extensively affected by the possibility of displacement of the government, which creates uncertainty and leads a sudden increase in the country's sovereign CDS spread.

1.2 EXTREME VALUE THEOREM

1.2.1 Introduction

Extreme events occur rarely but when they occur, the effects of the events are devastating. As in the 2008 financial crisis, major crises have strong and long-lasting effects over the whole economy. For this reason, studies for estimating rare events have been going on for many years. Extreme value theorem (EVT) provides a robust statistical theory to measure extreme risks. EVT is constructed on a highly sound statistical and mathematical theory. EVT creates a model to analyze the extreme events and focuses on only the tail part of the distribution instead of whole distribution.

Estimating extreme events is difficult because there are limited data due to the fact that rare events occur once in a very long-time interval. Thus, the amount of data required for accurate forecasting of rare events are extensive. For example, predicting major crises that occur a few times in a century requires centuries of evidence (Christoffersen et al., 1998). Hence, although EVT is a significant tool, the limitations of estimating rare events should also be considered.

1.2.2 Measuring Extreme Risks

One of the most used methods for measuring extreme risks is Value at Risk (VaR), which is based on extreme value quantile estimation. VaR identifies the maximum possible loss, which can be faced in a fixed time interval when a certain probability given. VaR is extensively used as a risk measurement tool both by regulators such as Basel Committee on Banking Supervision or portfolio managers for risk management.

The variance-covariance approach, the Monte Carlo simulation, and the historical simulation approach are techniques that are widely used to estimate VaR. In the estimation of VaR, parametric models such as the variance covariance approach are generally criticized extensively for its normal distribution assumption. VaR underestimates the existing risk in the fat-tail financial time series with the normality assumption. Non-parametric methods such as the Monte Carlo simulation and the historical simulation approach do not make assumptions about the empirical distribution, but since they are not parametric, they have lower performance at the out-of-sample estimation.

VaR measure provides information on the probabilities of the potential loss but does not provide information on the amount of damage when the risk is realized. Thus, the question of "how bad is bad" is not answered by the VaR method. In this concept, Artzner et al. (1999) identified the criteria that should be in a coherent risk measurement and showed that the VaR method is not coherent since it does not meet the subadditivity criterion. When the subadditivity criterion is not provided, the VaR method generates an aggregation problem even if the risks are independent. Thus, in the case of risk diversification, the risk increases so VaR does not encourage diversification. Therefore, the expected shortfall (ES) method, which was developed as a consistent risk measure, has been used especially in the calculation of capital requirement.

Efforts to improve alternative VaR estimation methods are ongoing. For example, Berardi et al. (2002) suggested an alternative VaR estimation based on Kalman filter to estimate the portfolio, and since this approach is a recursive method, which considers each additional information dynamically, it is more sensitive to market volatility. A wide range of surveys on VaR methods and new measurement methods of VaR are found in the literature. Some examples are nonparametric estimators for conditional value-at-risk and conditional expected shortfall (Martins-Filho et al., 2018), an alternative risk measure to VaR, which was termed as mark to market value at risk (MMVaR) (Chen et al, 2019), and a combination of VaR forecasts with penalized quantile regressions. (Bayer, 2018)

We noted that one of the main disadvantages of the traditional VaR method is the assumption of normal distribution. If the empirical distribution is not normal, the performance of the extreme risk estimation is expected to be low. Considering the financial time series is stylized to be fat tail and asymmetric, the risk is underestimated with traditional methods. To cope with this disadvantage, methods of estimating VaR based on the EVT method have been developed.

1.2.3 Extreme Value Theorem Methods

EVT mainly uses two main methods: block maxima method (BMM) and peak over threshold (POT) method. In the block maxima method, the time series is divided by consecutive fixed intervals and the maximum value in each subsample is taken to estimate extreme values. Using these data, the generalized extreme value (GEV) distribution is fitted to the extreme values obtained.

In the peak over threshold method, the prediction is made using the exceedances above a certain threshold. These values are fitted into the Generalized Pareto Distribution (GPD). According to the Pickand-Balkema-Haan theorem (Balkema and de Haan 1974, Pickands 1975), exceedances over threshold converges to the GPD giving a sufficiently high threshold.

The pareto type distribution is used in the financial extreme risk analyses since the extreme events are weighted more compared to the normal distribution by assigning more probability to the extreme events at the tail (Gourieroux & Joann, 2001). On the other hand, one of the critical problems in the estimation with the POT method is to find the appropriate threshold value. When the threshold value is too low, it reduces the success in measuring extreme risks, while too high threshold values reduce the effectiveness of the analysis by reducing the number of data and making it difficult to fit the GPD distribution. This issue is called as *"a bias-variance tradeoff"* in the EVT literature.

There are several approaches for determining the appropriate threshold value. In this study, the mean excess plot method will be used to find the optimal threshold value for the sovereign CDS series. The mean excess plot method has been used by many studies (Gilli and Këllezi, 2006, Allen et al.,2013, Skřivánková and Juhás, 2012,). In this method, the region where the mean excess function is approximately linear is selected. This area gives a reasonable range of exceedances to converge GPD.

In this method, after the tail part of the distribution is taken, the residuals are fitted to the GPD distribution instead of the direct empirical estimation. The reason for this is that it is difficult to make an estimation based on the empirical distribution, especially if the data remaining after the exceedances are taken are rather limited.

Likewise, one of the problems encountered in the BMM method is the determination of the appropriate block interval. If the block interval is too large, the number of data involved will be small, but if the interval is too narrow, the dataset will include non-extreme values.

Although the BMM and the POT method have the above-mentioned advantages and disadvantages, the POT method is preferred recently since it allows the effective use of the existing data. On the other hand, if the data set is large enough, the BMM method may be preferred as it does not cause data clustering problems when the blocks are large enough (Gilli and Këllezi, 2006).

An example of the application of the Generalized Extreme Value (GEV) was modeled by Makhwiting et al. (2014). They analyzed the daily returns of the Johannesburg Stock Exchange (JSE) using the Generalized Extreme Value (GEV) distribution and suggested that GEV distribution was a good fit for the above-mentioned data set.

Empirical studies show that comparing with the block maxima method, the peak over threshold (POT) method shows superior performance in estimating extreme values. Gilli and Këllezi (2006) applied the extreme value theorem to calculate VaR and ES using both the BMM and the POT method on 6 market indices, namely S&P500, FTSE 100, Hang Seng 50 (HS50), DJ Euro Stoxx 50 (ES50), Nikkei, and the Swiss Market Index (SMI). Since the POT method uses the data more effectively, they reached the conclusion that the POT method was superior.

EVT has been utilized in a wide range of applications such as insurance, finance, and agriculture. Skřivánková and Juhás (2012) applied EVT in the analysis of extreme car insurance claims from a Slovak insurance company to determine the appropriate threshold level for reinsurance. Younes Bensalah (2000) calculated VaR for a series of daily Exchange rates of Canadian/US dollars over a 5-year period using the EVT technique. Odening and Hinrichs (2003) applied EVT to evaluate the appropriateness of EVT in evaluating market risk in the agricultural sector, where the time horizon is longer than that of financial markets. In the extreme quantiles (99% and higher), they concluded that EVT is an effective estimation method.

Gençay et al. (2003) compared EVT with the methods such as GARCH (Generalized AutoRegressive Conditional Heteroskedasticity), variance-covariance (Var-Cov), and historical simulation, as well as adaptive GPD (using sliding window) and non-adaptive GPD methods for a variety of quantiles from Borsa Istanbul (Türkiye) and S&P 500 data. In this context, GARCH models lead to a significant volatile quantile estimation as compared to other models. In other words, other models yield a more stable quantile estimation. Furthermore, it is seen that the GPD model is preferred for the most of the quantiles in performance comparison based on the 'violation ratio' in the backtesting method.

EVT also can be used as a tool to examine extreme loss and extreme return probabilities; in other words, the left tail and the right tail parameters can be compared in the given assets. Gençay & Selçuk (2004) used the EVT method to investigate emerging economies and found that risk and reward probabilities were not evenly distributed in these countries since the left tail and right tail parameters were not alike. They reported that the GPD model gives the best results especially in very high quantiles when compared to other VaR calculation methods. Onour, I. A. (2010) estimated VaR values using the EVT method for the stock markets of the Gulf Cooperation Council (GCC) countries and compared the right tail and left tail parameters for GCC markets and S&P 500 stock returns.

Various studies have investigated whether EVT is a more effective estimation method in usual economic conditions or in crisis periods. Andjelic et al. (2010) studied four emerging market countries, namely Serbia, Croatia, Slovenia, and Hungary, to test the performance of the EVT method for developing countries and concluded that EVT is a better estimation measure during periods in which the series are more stable, with no profound changes.

There are studies focusing on increasing the effectiveness of the EVT method. In the estimation of VaR using the EVT method, the Maximum Likelihood Estimator (MLE) is generally used. However, the MLE is not very robust since it is sensitive to a few exceedances. Trzpiot and Majewska (2010) suggested a robust estimator and found that this method generates more accurate results based on empirical consequences of selected market indices.

1.2.4 Dynamic EVT-VaR Approach

It appears that high-frequency financial data are conditionally heteroscedastic and thus the assumption that data are independent and identically distributed in the classical EVT theory is not valid. One of the most important assumptions of EVT that the data are independent and identically distributed (IDD), which is not valid in the real-life practices, negatively affects the reliability of the results. This situation has been criticized for reducing the reliability of one of the EVT theories in real life exercises and causing a deficient performance in yielding results (Diebold et al., 1998).

McNeil & Frey (2000) proposed a two-stage Dynamic VaR-EVT approach. In this method, the residuals are obtained by fitting the GARCH model to the time series in the first stage and then the time-varying EVT-VaR technique is applied on the residuals. The dynamic EVT-VaR method performs better when compared to other methods. Also, using the rolling window method, it is possible to make a more accurate estimation utilizing the latest information in the subsequent window. On the other hand, one of the disadvantages of this method is that it requires a large amount of data to be used. However, the data used in the EVT method over a certain threshold are limited. Since the rolling window method does not use all the data in the data set, it introduces an additional limitation on the analysis of the existing data.

The dynamic EVT-VaR method has been applied in many developed and emerging market economies and compared with other methods. In this context, a large literature has emerged suggesting that the predictive performance of the dynamic EVT-VaR method is superior. The dynamic EVT method is more successful in anticipating extreme risks because it responds quickly to the changing market conditions.

The GARCH method is used extensively as a tool of risk estimation. However, one of the most important disadvantages of the GARCH method is that it leads to a very volatile quantile estimation (Gençay et al., 2013). In application, 1-day volatility is multiplied by the scaling factor (square root of time horizon) to find the n-day volatility, which is called as the "square-root-of-time rule". However, in the GARCH method, scaling factor increases volatility fluctuation. As the forecast horizon increases, this effect enlarges correspondingly, thus the estimation power of volatility models decreases. Especially when the forecast horizon surpasses a few weeks, estimating power of volatility models decreases (Christoffersen et al, 1998). Hence, it is recommended to apply the EVT method, which provides more reliable results in relatively long-term forecasting, especially as a tool of risk management.

Emerging economies have different stylized facts than developed economies. For example, emerging economies have a more volatile market structure and crises have more contagious effects on each-other (Andjelic et al., 2010). Since it is more important to measure and follow the market risk in these economies, studies on applying Dynamic -EVT on emerging economies are widespread. Ozun et al. (2007) applied filtered (conditional quantile) EVT method for Türkiye stock market to show that the performance of the filtered ES is better when the predictive performance is compared with the different GARCH models using various backtesting algorithms. Likewise, Karmakar (2013) validated the accuracy and reliability of the 2-stage conditional EVT-VaR method in different quantiles and for both negative and positive returns using the SENSEX (Bombay Stock Exchange Sensitive Price Index) data generated by Bombay Stock Exchange, India.

Since emerging market economies are particularly volatile, studies to improve the EVT method in application to these markets are ongoing. For example, Radivojevic et al. (2016) proposed a new hybrid model based on the application of AR (p) -GARCH (1,1) model to adequately capture the conditional volatility in emerging markets.

Dynamic-EVT was applied in crisis and normal periods to test the validity of the method in many studies. Uppal and Mangla (2013) showed that the dynamic-EVT method outperformed other VaR estimation methods, both in normal market conditions and in extreme market conditions such as global financial crisis. Uppal and Mangla (2013) applied the EVT method for developed and leading developing countries for both pre-crisis and crisis periods. When these two periods are compared, it is seen that the distribution is even more fat tail in the crise periods than the normal periods, which justifies the use of EVT. However, the empirical study pointed out that the EVT parameters predicted in pre-crisis and crisis periods were different from each other, and therefore EVT could not provide a sufficiently reliable estimate especially in financial turbulence periods such as global financial crises.

Lastly, in one of the early applications of the Dynamic-EVT method on CDS, they find that filtered GARCH residuals are not IDD. Moloney & Raghavendra (2010) obtained GARCH residues to implement the EVT method for selected CDS market returns but stated that for the given CDS data sets and time interval, residuals were not IDD. Thus, they concluded that there may be limitations on applying the GARCH-EVT approach for risk measurement in the CDS markets.

The dynamic EVT method, as known as Conditional EVT (C-EVT) in some sources, is applied as a standard method in financial risk management. Work is underway to develop the performance of the standard C-EVT method with various innovations. M. Bee et al. (2016) proposed the realized volatility EVT (RV-EVT) model, in which the two-stage EVT approach was filtered with a high-frequency based volatility model instead of GARCH-type filtering in the first stage and then POT method was applied to the residuals. Although the GARCH-type filtering used in the standard C-EVT method is better in the first stage, the RV-EVT method performs better in terms of risk management than the C-EVT method in predicting long-term VaR.

1.3 CONNECTEDNESS

1.3.1 Introduction

As different countries and markets depend on each other in a certain degree, an event occurring in one of these markets significantly affects others. The increase in the dependence between markets, especially in times of crisis, requires investors and policymakers to regularly monitor the interdependence among those markets. Thus, the monitoring of contagion and spillover effects and the degree of the interdependence among the markets are gaining importance. Many methods have been used to measure the dependence among the markets and the change of this interdependence over time. In this study, after summarizing the methods used in the literature, the extended joint connectedness method will be used.

1.3.2 Connectedness Approaches

Due to capital mobility and financial integration that occur because of globalization, financial markets affect each other very quickly. Diebold and Yılmaz (2009) proposed the connectedness approach to measure the connectivity between markets. This method, which is quite intuitive, has been used in many studies in the fields of economics and finance, and over time the model has been further developed in many respects.

Connectedness analysis is widely used in the literature because of its distinct advantages. It is applied to measure spillover effects among different countries and markets. Guimaraes-Filho and Hong (2016) measured dynamic connectedness of equity markets in Asia based on Diebold and Yilmaz (2012). In this analysis, generalized VAR framework was used for the forecast-error variance decomposition to be invariant of the ordering of variables. They reported that the aggregate equity returns and volatility connectedness increased significantly after the global financial crisis (GFC). In addition, following GFC, in all countries, especially in Asia, while emerging countries have become net shock transmitters, developed countries increasingly have turned out to be net shock receivers. The connectedness between Hong Kong, which serves as a regional financial hub for Asia, and China has increased in the last decades with the increased financial integration of China with other markets.

Analyses indicate that spillover increases in times of crisis, as well as in certain period just before the crisis. Ferrerira et al (2021), using the correlation coefficients obtained from the Detrended Cross-Correlation Analysis and creating a network with the sliding window method, also examined the behavior of the network in different time zones. In this study conducted with 13 stock market data covering 1998-2013, they observed in parallel with other studies that connectivity increased before and during the crisis. This relationship between financial crises and increased connectivity demonstrates the opportunity to predict major financial crises and take measures to avoid them.

Connectedness Analysis has attracted a great deal of attention in recent years since researchers have a chance to apply it in many fields of economics and finance. One of the difficulties encountered in the connectedness analysis is that when the number of variables is too large, the model becomes complex and makes it difficult to interpret. Meglioli et al. (2021) expanded the analysis of connectedness by making it multi-level by distinguishing macro-level and local-level networks. In this study, the macro-level network indicates variables a global level effect, while the local-level network displays variables with an only local level effect, such as small or closed country variables. In this method, while performing a local-level analysis, they considered macro-level variables as exogenous, thus significantly reduced the number of parameters. Zhang et al. (2020), on the other hand, made a tail risk connectedness analysis by dividing the sectors into four separate spillover function blocks in their analysis on Chinese sectors using the block model.

In the study on sovereign CDS connectedness by Boyrie and Pavlova (2015), the DY (2012) and Principal Component Analysis were used for the period between 4 January 2010 and 11 July 2014 on BRICS and MIST countries. Boyrie and Pavlova (2015) found that the BRICS group was dominated by Brazil and the MIST group was dominated by Mexico. They also concluded that global financial factors have little effect on sovereign CDS. This thesis also analyzes the sovereign CDS connectedness of the BRICS and MIST countries, the effects of global risk factors, and uses the PCA method following the similar steps with Boyrie and Pavlova (2015). However, this thesis differs from Boyrie and Pavlova (2015) in many aspects such as the period in which the analysis was made, the way the analysis was conducted, and because we investigated the extreme risk connectedness of sovereign CDS.

The different agents in the economy are behaving heterogeneous in different time intervals. For example, when there is a shock in the stock market, there may be short-term responses based on portfolio adjustment or long-term responses resulting from a permanent change in expectations. The decomposition of short, medium, and long-term connectedness in markets provides a rich source of information for investors and economists.

Barunik and Krehlik (2015) proposed a framework to measure connectedness in frequency domain. They interested in the amount of forecast error variance at different frequency bands. To find frequency measure, they used Fourier transformations of the impulse-response functions. They found the short-, medium-, and long-term effects of the shocks by spectral representation of the forecast error variance decomposition. When we aggregate these different time horizons, we obtain Diebold and Yilmaz total connectedness measure, so frequency connectedness provides additional rich economic analysis material without loss of the present total connectedness data.

The frequency connectedness between major assets in the US stock market was analyzed by Barunik and Krehlik (2015). Connectedness in the US stock market is mainly driven by high frequencies from 1 day to 1 month, but in the global financial crisis, the structural change occurred, and low frequency has played an important role during this period. This shows that the US stock market responded to the new information very quickly in the short term. This result also confirms that long term connectedness plays a predominant role in crisis period due to the increased uncertainties and deteriorations in the long-term expectations.

Barunik and Kocenda (2018) examined the total, asymmetric, and frequency connectedness between oil and forex markets. When the total connectedness is examined, it is seen that connectedness was lower than that in the forex market itself when the oil market was added, except for the year 2012, when oil prices were historically high.

Asymmetric connectedness analyzes the potential asymmetries in the connectedness by decomposing the effects of the negative and the positive shocks. With the help of ‘the realized semivariances’, it is possible to differentiate the effects of negative and positive shocks. Bad volatility (negative shocks) has been observed to be effective in the Forex market throughout the analysis. When the oil price market is added to the Forex market analysis, it is seen that it reversed and good volatility became dominant. When frequency connectedness is examined, it is seen that high frequency connectedness was generally low during the analysis term, and long-term connectedness increased significantly in the period of global financial crisis, European debt crisis, and oil price decline in 2014.

The COVID-19 pandemic has had an extremely negative impact on the economies of the countries, as well as other devastating effects. For example, Polat (2021) analyzed the systemic risk contamination issue for the euro area, utilizing both the DY and frequency connectedness methods, through the use of the daily Composite Indicator of Systemic Stress (CISS) data. As a result of this study, it was concluded that the systemic risk transmission increased significantly because of the Covid-19 pandemic, despite the stimulus measures taken by the governments.

In the approach proposed by Diebold and Yilmaz (2012, 2014), the change in the level of connectedness over time was demonstrated using the rolling window approach as well as static connectedness. Antonakakis and Gaubauer (2017) performed the Dynamic Connectedness Analysis using the TVP-VAR model. The most important advantages of the TVP-VAR method compared to the rolling window method applied by DY are that there is no need to choose a random window size and that it avoids losing data as large as the window size. In addition, the TVP-VAR approach is less sensitive to the effects of outliers.

Another group of connectedness methods developed to solve the dimensionality problem are Dynamic Elastic Net, Lasso and Ridge Vector Autoregressive Models. While calculating connectedness with this method, shrinkage effects, which are Elastic Net, Lasso and Ridge models, are included in the estimation of the Vector Autoregressive Model. Demirer et al. (2015) first introduced the penalized connectedness to solve the dimensionality problem. To estimate the high dimensional VAR model, adaptive elastic net model is used.

Demirer et al. (2017) applied the penalized VAR model on global bank network connectedness. They reach the conclusion that the measure of connectedness reached its highest level at the Lehman bankruptcy on September 15, 2008. Then the connectedness soared because of the two waves of European dept crisis.

Gabauer et al. (2020) performed the dynamic elastic net, lasso and ridge connectedness analysis using the U.S. Housing Price data. According to the results of this study, since the VAR parameters vary between 0 and 1 and the square of the parameter is taken in the Ridge regression, the penalty effect becomes an even smaller number, so it cannot be effective. On the other hand, lasso regression models are more effective since the absolute value of the parameter is taken in the VAR application. For this reason, since it gives more weight to the Lasso coefficient than the Ridge coefficient in the calculation of the elastic net, it makes a close estimation to the Lasso regression. If we summarize the results of the empirical application, all the shrinkage models (elastic net ridge and lasso) give similar results until 2007 in the U.S. housing market while the OLS (Ordinary Least Squares regression) results (no penalty used) give a higher connectedness value than the others. However, during the crisis, all the measurements of connectedness methods mentioned above give similar results.

The Cholesky decomposition identification scheme was used in the originally proposed Diebold and Yılmaz (2009) approach. However, due to the ordering problem, the generalized variance decompositions approach was used as the decomposition scheme in Diebold and Yılmaz (2012). Since the variables in the Cholesky decomposition are orthogonalized, the variables are statistically independent, whereas there is a correlation between the variables in the generalized variance decompositions approach. The fact that this correlation between the variables is not considered in the model estimation causes the connectedness to be found underestimated or overestimated, depending on the direction of the correlation.

To solve the correlation problem, the joint spillover index method was proposed by Lastrapes and Wiesen (2020) as an alternative connectedness method that considers the correlation between the variables. Since the sum of the relative effect of a variable does not have to be equal to 1 in the joint spillover connectedness approach, there is a problem in calculating the net directional connectedness value. The TVP-VAR Extended Joint Connectedness Approach, which is also used in this study, was proposed by Balcilar et al (2020) to overcome this problem.

1.3.3 Extreme Risk Spillover Analysis

There has been an increase in studies aimed at predicting extreme risk spillover recently. It can be misleading for political decision makers and portfolio managers to just look at the correlation between markets. It is important to determine how the risk has spread to other markets including the direction and speed of its spread. In addition, the rapid contagion of risk which would occur in extreme market conditions could have a devastating effect on the market much more than expected. When the co-movement between various markets increases, the potential benefits of diversification are eliminated. For this reason, estimating the spillover effects between markets correctly prevents a false sense of protection.

Examining extreme tail risk behaviors between markets prevents underestimating the existing risks. In addition, while there are studies on extreme risk spillovers in stock markets in different regions, studies on extreme risk spillovers in CDS are limited. This thesis proposes a novel hybrid model which combines the Dynamic EVT-VaR approach with VAR model applications. This approach expands the existing applications in extreme risk spillover studies and applies the model on sovereign CDS spreads.

Some of the studies perform extreme risk spillover analysis by applying the granger causality approach. These studies are especially important in determining the markets that are the pioneers in inter-market spillover effects. Thus, it is recommended for policymakers and portfolio managers to monitor the leading markets and use their risk measures as an early warning mechanism. Monitoring more effective markets that lead others provide early information about potential developments in other markets. Using the Granger causality in the risk approach, Wang et al. (2016) examined the interaction between major gold markets. In this article, downside and upside VaR values were calculated using the variance-covariance approach and the reliability of these VaR values was evaluated. Then, they analyzed it using extreme risk spillover granger causality. Overall, the downside risk was found to be greater than the upside risk and it was transmitted more after the global financial crisis.

One of the disadvantages of Granger causality in risk approach in calculating extreme risk spillovers is that it does not allow multivariate analysis since the analyses are performed with market pairs. In addition, although it gives information about whether the directions of extreme risk spillovers are significant or not, a comparison cannot be made by directly measuring the size of the extreme risk spillovers between market pairs.

Risk spillover values were evaluated by calculating the downside and upside Conditional Value-at-Risk (CoVaR) in studies conducted within the scope of extreme risk spillovers. While Value at Risk (VaR) calculates the risk value in an isolated market, with CoVar calculation, the VaR value of one market is calculated conditional on the VaR value of the other market. In this method, the change of extreme tail behaviors between markets over time is analyzed using dynamic copula. This method gives information about the potential loss/gain situation that may occur in one market against developments/events in another market. Warshaw (2019) examined the dynamic dependence structures of extreme tail behavior of the North American equity market pairs using the Generalized Autoregressive Score (GAS) copula model. In this context, it is seen that tail dependence increased during the Global Financial Crisis (GFC) periods for all market pairs. It has also been shown that the downside and upside risk spillovers are asymmetrical, and the downside spillover is significantly higher than the upside spillover in all market types and in all conditioning aspects. These results demonstrate that the possibility of these countries' markets to act together increases especially in the times of crisis. In addition, it is seen that the spillover aspects also differ between country pairs. It is observed that the risk spillovers are especially higher from developed countries to developing countries. This difference varies according to the size and development of the market pairs' development differences.

The extreme risk spillover between the Maritime market and commodity prices has been analyzed by calculating CoVaR by Sun et al (2020). First, in this study, it was seen that the absolute CoVaR values for the fright market were systematically higher than the unconditional VaR values. It was found that extreme movements in the commodity market, especially in the oil market, had a strong spillover effect on maritime returns. Although the CoVaR approach calculated using the Generalized Autoregressive Score (GAS) copula provides a very robust structure for the calculation of extreme risk spillover pairs, this method is a limited approach as it is generally applied only for market pairs. For this reason, it does not constitute a multivariate model structure that considers the effects of all analyzed markets simultaneously in the calculation of the extreme tail risks.

A quantile variance decomposition framework method has been developed recently for measuring extreme tail risk spillover. In this method proposed by Su (2019), the connectedness values applied by Diebold and Yilmaz (2009) was calculated by means of a quantile regression method for different quantiles. This model was applied in the calculation of the spillover index between G7 and BRICS stock markets. In line with other studies, in this study, while developed economies have a positive net risk spillover effect, it is seen that the net risk spillover effect for developing countries is negative. In other words, the risk spillover generally occurs from developed markets to emerging markets. One of the most important results of this study is that the calculated extreme risk spillover values are considerably above the volatility spillover values. This result shows that volatility spillover values which do not consider extreme risk spillover, as widely used in the assessment of risks, underestimate the existing risk spillovers, and therefore, they are not reliable.

CHAPTER 2

DATA AND METHODOLOGY

This study evaluates the extreme risk connectedness of sovereign CDS data in BRICS and MIST economies. When there is an exogenous shock on sovereign CDS in one country, the exogenous shocks on all other countries are estimated by the Vector Autoregression (VAR) model. The effect of external shocks on sovereign CDS is discussed with the connectedness approach, and the transmitting mechanism between them is discussed in this study. Sovereign CDSs are closely watched by both investors and policy makers as one of the most important tools that show the economic sustainability of a country. With the Connectedness approach, countries that are the main transmitters of shocks should be determined and policy makers and investors in other countries should take precautions by closely following the financial structures of these countries.

2.1 DATA

In this study, daily log-return of 5-year US Dollar sovereign CDS data from March 18, 2011 to June 1,2022 are examined for BRICS and MIST countries. Since India's sovereign CDS is not available for a long-term period, following Boyrie and Pavlova, 2015 and Stolbov, 2014, we used the State Bank of India five-year CDS as a proxy.

Also, to analyze the global factors on BRICS and MIST countries' sovereign CDS, S&P 500 and MSCI EM Indices and volatility indices, namely VIX and VSTOXX Indices, were used. In addition, the effects of the other countries' CDS on BRICS and MIST Countries were analyzed using the principal component analysis (PCA). We used the PCA for BRICS, MIST, EU, Asian, and Latin American countries. Based on the data availability for the time horizon of this study, five-year sovereign CDS spreads of the following counties were used: EU countries, Austria, Belgium, Croatia, Denmark, Greece, Finland, France, Germany, Hungary, Ireland, Italy, Lithuania, Netherlands, Poland, Portugal, Romania, Spain and Sweden; Asian countries, Malaysia, Philippines, Thailand, Vietnam, Kazakhstan, Hong Kong, Pakistan, Lebanon and Japan, and Latin American countries, Chile, Colombia, and Peru.

Countries are determined based on the data availability and the properties of the data. For the sovereign CDS data, if there is no purchase for that day, the value of the spread stayed same for those days. When we take the log- difference of these time series, the data had zero values for a long time. Since we use the rolling window for EVT-VaR analysis and used only 10 percent of the data for that specific window to take the extreme values, the solution matrix would be indefinite. Therefore, we did not include the sovereign CDS data of these countries.

Another issue is that if the country defaults such as in the case of Argentina, there is no market trading for a long time after the default; therefore, the EVT-VaR values of the series cannot be calculated for those time horizons. Therefore, we did not include those countries with missing data for a long period of time because of the default event. Greece is in a similar situation, but the amount of missing data in the Greek sovereign CDS does not prevent the EVT-VaR analysis. Data used in this thesis were obtained from "*Refinitiv Eikon"* terminals.

Table 1 shows the raw sovereign credit default swap spread data of BRICS and MIST countries. When the table is examined, it is seen that the countries with the highest mean are Russia, Türkiye, and South Africa, in descending order. Countries with the minimum average spread values are South Korea, China, and Mexico. The main reason why countries have high spreads on average is generally the debt crises and political instability they have experienced.

As a result of the Covid 19 pandemic, an increase was observed in the SCDS values for developing countries, but this increase was not permanent. The most important reason for the rise of sovereign CDSs in recent years is the Russian war in Ukraine. Within the framework of the period covered, the Russian sovereign CDS spreads increased up to 13 822.

As expected, while sovereign CDS values in relatively developed countries remain low, these values are quite high for developing countries. In addition, as seen in Figure 3, country-specific variations are very significant in determining the value of a particular country.

Figures 1 and 2 show sovereign CDSs for BRICS and MIST countries, respectively. When these figures are examined, it is seen that countries generally follow a similar pattern over time.

One of the most important stylized facts of financial data is that it is a fat-tail. When the Q-Q plot in Figure 4 is examined, the sovereign CDSs are not normally distributed and Figure 5, which shows sovereign CDSs log-return series, reveals that there is heteroskedasticity. This situation justifies the use of the EVT approach in calculating extreme risks in sovereign CDS data. It was proven that the EVT approach is effective in series with heavy tailed distribution, as in the financial data.

Table 1: Sovereign Credit Default Swap Summary Statistics

	Brazil	**China**	**India**	**Indonesia**	**Korea**	**Mexico**	**Russia**	**South Africa**	**Turkey**
nbr.na	3.00	7.00	11.00	3.00	4.00	4.00	41.00	2.00	3.00
min	92.06	29.08	70.58	59.06	17.94	64.17	54.64	114.32	109.82
max	521.36	199.57	405.00	306.77	234.73	309.16	13822.99	492.47	726.41
range	429.30	170.49	334.42	247.71	216.79	244.99	13768.35	378.15	616.59
median	182.30	71.48	154.05	137.14	52.29	113.80	162.25	196.41	250.44
mean	200.77	76.78	167.85	141.62	57.95	120.89	304.47	205.32	287.56
SE.mean	1.47	0.56	1.45	0.92	0.61	0.61	20.52	0.98	2.31
CI.mean 0.95	2.88	1.10	2.83	1.81	1.21	1.19	40.23	1.93	4.53
std.dev	79.46	30.40	78.00	49.78	33.22	32.84	1101.72	53.07	124.87
coef.var	0.40	0.40	0.46	0.35	0.57	0.27	3.62	0.26	0.43
skewness	1.50	0.52	1.01	0.50	1.52	1.51	9.88	1.44	1.09
kurtosis	2.60	-0.36	0.13	-0.41	2.61	4.13	102.39	2.97	0.53

Figure 1: Sovereign Credit Default Swaps for BRICS countries

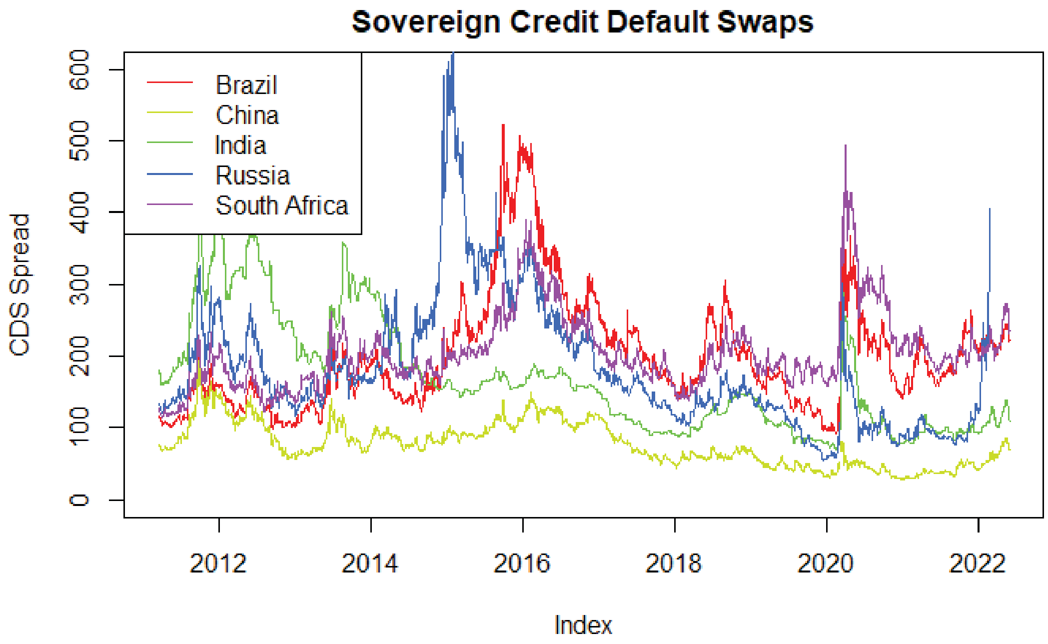


Figure 2: Sovereign Credit Default Swaps for MIST countries

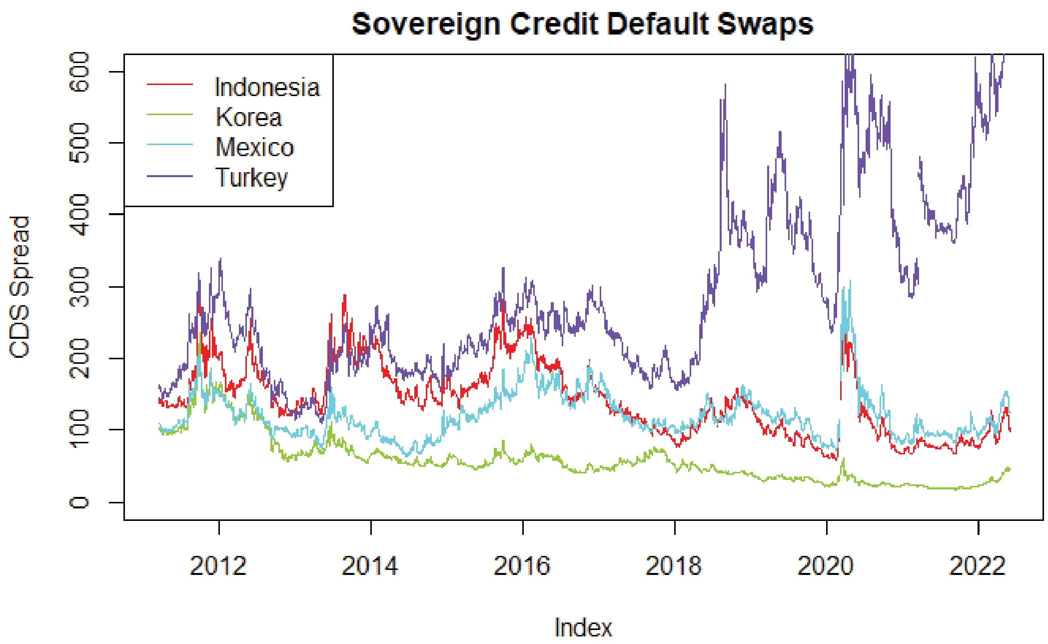


Figure 3: Sovereign Credit Default Swaps of BRICS and MIST Countries

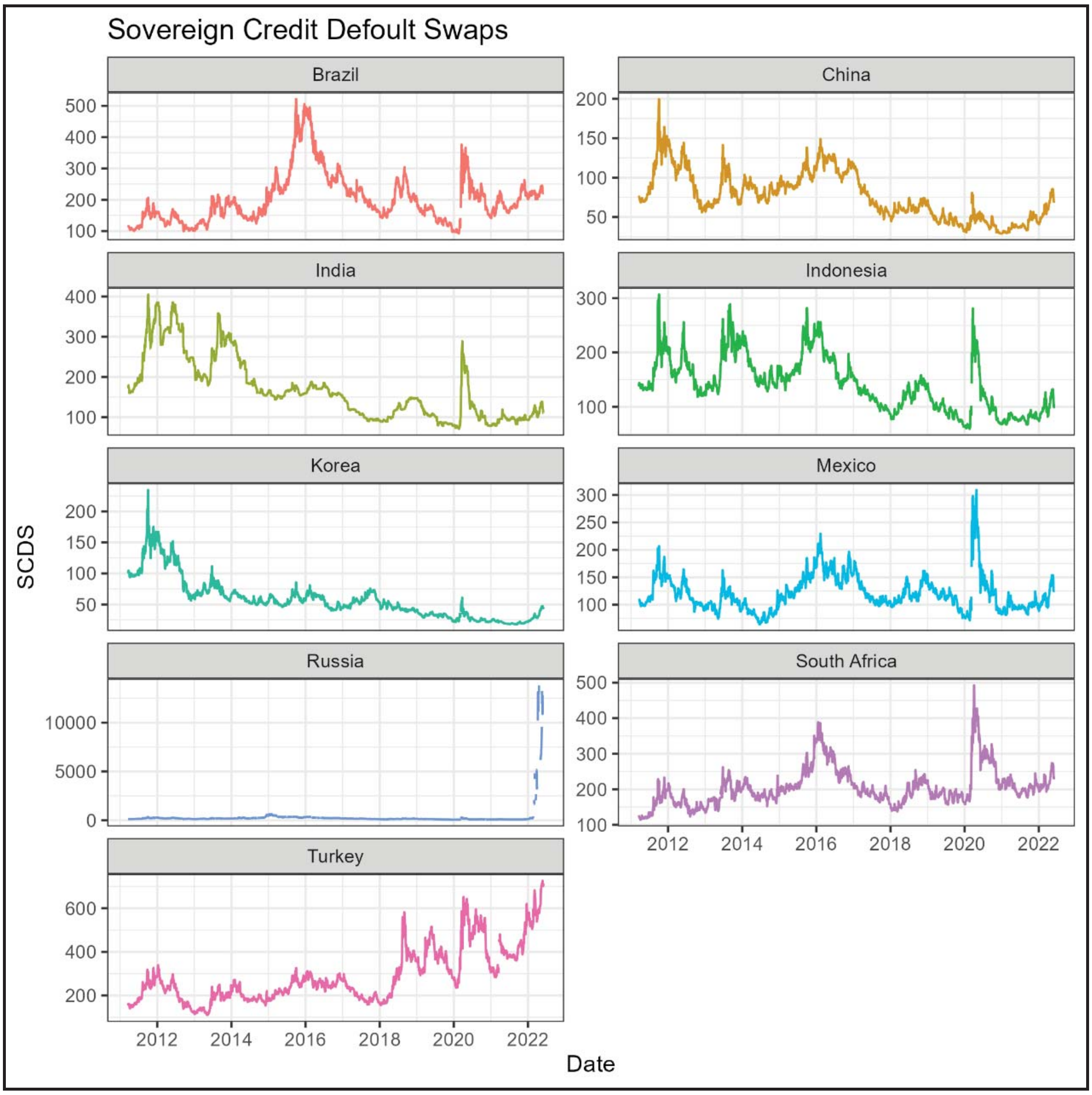


Figure 4: Q-Q Plots for Sovereign Credit Default Swaps

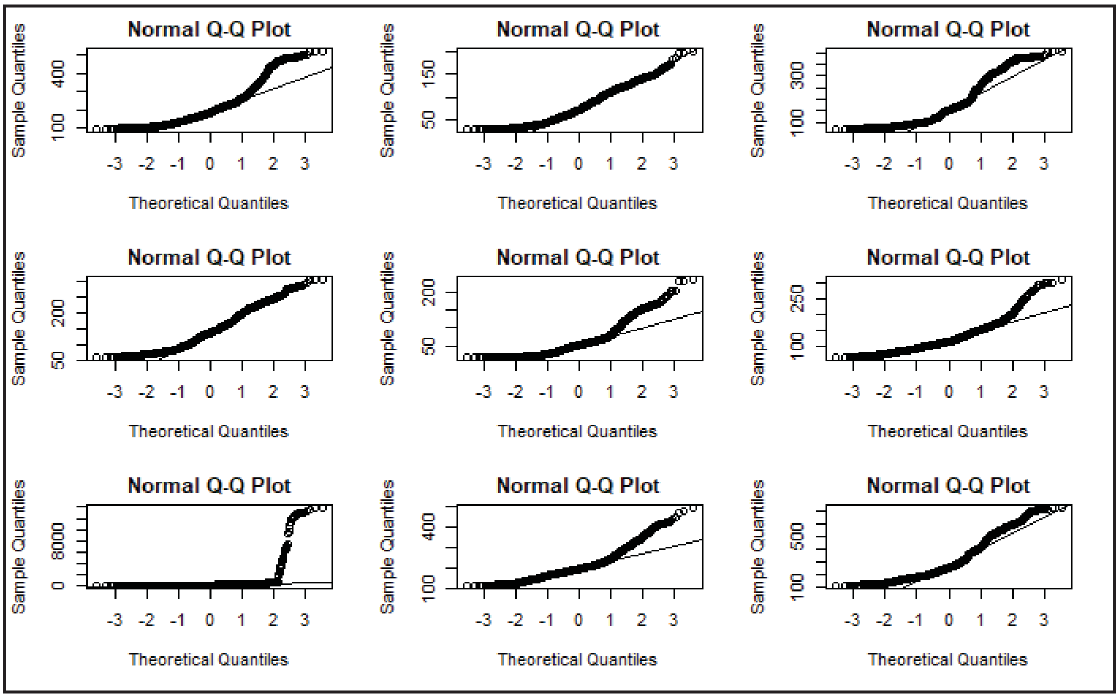
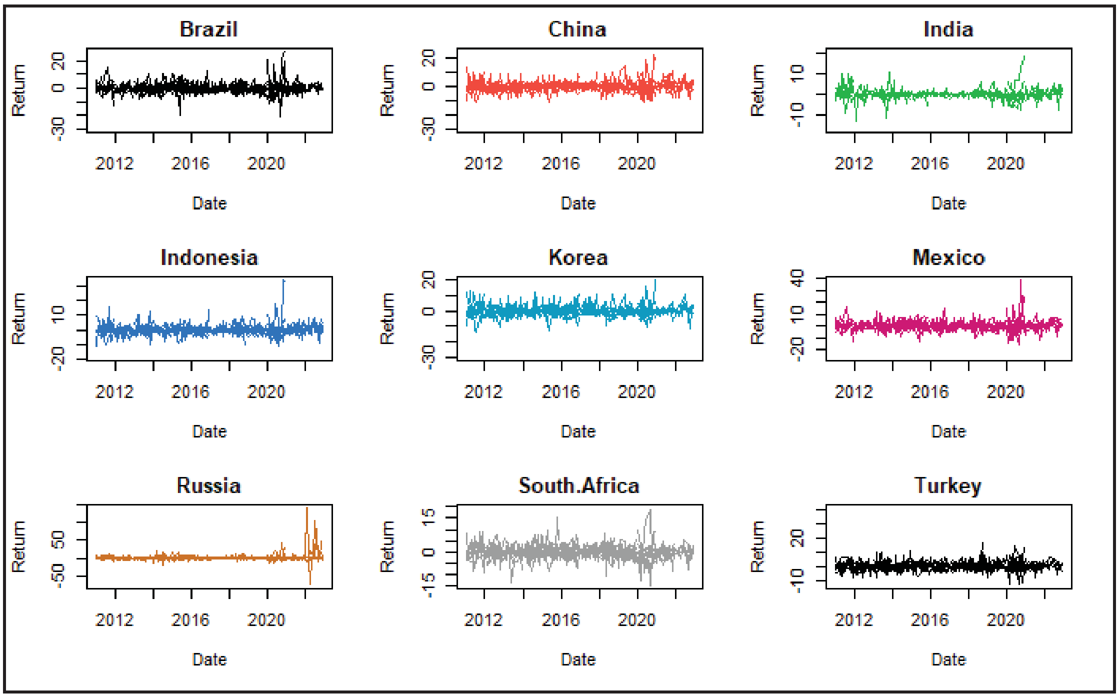


Figure 5: Sovereign Credit Default Swaps Log-Return Series



2.2 METHODOLOGY

2.2.1 Extreme Value Theorem

In this thesis, the dynamic EVT-VaR approach will be used to find an extreme risk measure. Chapter 10 of the Singh and Allen (2017) was benefited for the R codes of the dynamic EVT-VaR Model.

Empirical studies show that high-frequency financial data are conditionally heteroscedastic and thus the assumption that data are independent and identically distributed in the classical EVT theory is not valid. For that reason, in this thesis, the dynamic EVT-VaR approach is used to find an extreme risk measure. A literature review regarding EVT suggests strongly that the dynamic EVT method performs better than other methods. dynamic EVT-VaR series are calculated by applying the GARCH (1,1) method in filtering the sovereign CDS series, and then the GPD method is applied to the residuals.

The dynamic-EVT method is a semi-nonparametric method based on the Peak Over Threshold approach. We can perform out-of-sample risk estimation by fitting the GPD distribution to the tail of the empirical distribution. In this method, after the tail part of the distribution is taken, the residuals are fitted to the GPD distribution instead of the direct empirical estimation. The reason for this is that it is difficult to make an estimation based on the empirical distribution, especially if the number of data remaining after the exceedances are taken is rather limited.

2.2.2 Connectedness Analysis

In this thesis, extreme risk connectedness of sovereign credit default swaps (SCDS) is estimated. Extreme risk of the SCDS of the countries is measured with the Dynamic-EVT method using the time-varying EVT-VaR values. Then, the connectedness of extreme risks is examined using the risk metrics we acquired from the EVT-VaR application.

Many methods have been used to measure the dependence among the markets and the change of this dependence over time. Connectedness analysis is widely used in the literature because of its distinct advantages. It is applied to measure spillover effects among different countries and markets. In this analysis, instead of the generalized VAR framework for the forecast-error variance decomposition, we applied the extended joint connectedness analysis to be able to comment on the effect of different countries' sovereign risks on other countries while considering the correlation between the contributing data.

2.2.2.1 Diebold and Yilmaz (DY) Connectedness Approach

The first model introduced by Diebold and Yılmaz (2009) showed the effect of aggregate spillover between markets by calculating a single spillover index using the variance decomposition of the Vector Autoregression (VAR) model. Variance decomposition enables the forecast error variance of each variable to be divided depending on many shocks in the system. Cholesky decomposition was used as an identification scheme in variance decomposition. For simplicity in calculating the spillover index, we start with covariance stationary first-order two-variable VAR as follows:

$$x_t = \Phi x_{t-1} + \epsilon_t$$

where $x_t = (x_{1t}, x_{1t})'$ and Φ is a 2x2 parameter matrix.

By covariance stationarity, the moving average representation of the VAR exists and is given by

$$x_t = \Theta(L)\epsilon_t$$

where $\Theta(L) = (1 - \Phi L)^{-1}$. Now rewrite the moving average representation as

$$x_t = A(L)u_t$$

where $A(L) = \Theta(L)Q_t^{-1}$, $u_t = Q_t\epsilon_t$, $E(u_t, u_t^{-1}) = I$ and Q_t^{-1} is the unique lower-triangular Cholesky factor of the covariance matrix of ϵ_t.

The optimal 1 step-ahead forecasting is

$$x_{t+1} = \Phi x_t$$

and corresponding 1-step ahead error vector

$$e_{t+1,t} = x_{t+1} - x_{t+1,t} = A_0 u_{t+1} = \begin{bmatrix} a_{0,11} & a_{0,12} \\ a_{0,21} & a_{0,22} \end{bmatrix} \begin{bmatrix} u_{1,t+1} \\ 2_{2,t+1} \end{bmatrix}$$

then covariance matrix

$$E(e_{t+1,t}, e'_{t+1,t}) = A_0 A'_0$$

Thus, the variance of the 1-step-ahead error in forecasting x_1t and x_2t is $a_{0,11}^2 + a_{0,11}^2$ and $a_{0,21}^2 + a_{0,22}^2$, respectively.

Spillover is then defined as the fraction of the 1-step-ahead error variances in forecasting x_i due to shocks to x_j, for i,j = 1,2. For two variable case; a_{0,21} is the contribution of x_1t shocks that affects the forecast error variance of x_2t and a_{0,12} is the contribution of x_2t shocks that affects the forecast error variance of x_1t. Thus, the total spillover is $a_{0,12}^2 + a_{0,21}^2$

Spillover index is then calculated as a share of the total spillover to the total error forecast variation $a_{0,11}^2 + a_{0,12}^2 + a_{0,21}^2 + a_{0,22}^2 = trace(A_0 A'_0)$.

Spillover index for first-order two variable VAR,

$$S = \frac{a_{0,12}^2 + a_{0,21}^2}{trace(A_0 A'_0)} . 100$$

Finally, the general case of p_th - order N-variable VAR, using H-step-ahead forecasts,

$$S = \frac{\sum_{h=0}^{H-1} \sum_{i,j=1,i\neq j}^{N} a_{h,ij}^2}{\sum_{h=0}^{H-1} trace(A_0 A_0')} . 100$$

The most important disadvantage of Cholesky decomposition is that it is order dependent, in other words, the spillover index values change when the order of the variables is altered. To use Cholesky decomposition, the variables must affect each other recursively as a chain. For this reason, a valid theory should lie under the variable order. Diebold and Yılmaz (2012) used the generalized vector autoregressive framework to produce the spillover index using invariant to ordering as a variance decomposition. In addition, while Diebold and Yılmaz (2009) calculated only the total spillover, Diebold and Yılmaz (2012) clearly defined the directional spillovers.

Diebold and Yılmaz (2012) used the generalized VAR framework of Koop, Pesaran and Potter (1996) and Pesaran and Shin (1998), after this invariant of ordering identification called KPSS (Kwiatkowski–Phillips–Schmidt–Shin is utilized.

The KPSS H-step-ahead error variance decompositions for H=1, 2,…, denoted by $\theta_{ij}^{g}(H)$

$$\theta_{ij}^{g}(H) = \frac{\sigma_j j^{-1} \sum_{h=0}^{H-1} (e_i' A_h \Sigma A_h' e_i)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma A_h' e_i)}$$

where Σ is the variance matrix of the error vectorε, σ_{ij} is the standard deviation of the error term for the i_{th} equation, and e_i is the selection vector, with 1 as the i_{th} element and zeros otherwise.

Diebold and Yılmaz (2012) conducted the normalization at the variance decomposition table by using row-sums. Thus, they ensured that the sum of the lines containing the elements in each row of the table is equal to 1.

Cholesky decomposition identification scheme orthogonalize shocks. In other words, the variables are statistically independent and do not affect each other. In contrast, VAR innovations using the generalized vector autoregressive framework for identification are contemporaneously correlated. Thus, the generalized approach allows correlated shocks. Since the shock to each variable is not orthogonalized, the sum of the contributions to the variance of forecast error is not necessarily equal to 1. Therefore, each element in the variance decomposition matrix is divided by row sum to perform normalization.

$$\widetilde{\theta_{ij}}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)}$$

where because of the normalization

$\sum_{j=1}^{N} \widetilde{\theta_{ij}}^{g}(H) = 1$ and $\sum_{i,j=1}^{N} \widetilde{\theta_{ij}}^{g}(H) = N$

2.2.2.2 Time Varying Connectedness (TVP-VAR Approach)

TVP-VAR model proposed by Antonakasiss et al. (2017) extends Diebold and Yılmaz (2004) that is based on generalized impulse response function (GIRF) and generalized forecast error variances decompositions (GFEVD) using the time-varying coefficients and time-varying variance-covariance matrices to perform dynamic spillover estimation.

We can explain the methodology of the TVP-VAR(p) model as follows:

$$y_t = A_t z_{t-1} + \epsilon_t \qquad \epsilon_t \mid \Omega_{t-1} \sim N(0, \Sigma_t)$$

$$vec(A_t) = vec(A_{t-1}) + \zeta_t \qquad \zeta_t \mid \Omega_{t-1} \sim N(0, \Xi_t)$$

with

$$z_{t-1} = \begin{pmatrix} y_{t-1} \\ y_{t-2} \\ . \\ . \\ . \\ y_{t-p} \end{pmatrix} \quad A' = \begin{pmatrix} A_{1t} \\ A_{2t} \\ \dots \\ A_{pt} \end{pmatrix}$$

where $\boldsymbol{y_t}$ and ϵ_t represents m x 1 vectors. The time-varying variance-covariance matrices $\boldsymbol{\Sigma_t}$ and $\boldsymbol{\Xi_t}$ are m x m and $\boldsymbol{m^2p}$ x $\boldsymbol{m^2p}$ matrices, respectively. $\boldsymbol{\Omega_{t-1}}$ represents all information available until t-1.

Time varying connectedness approach allows the variance-covariance matrix to vary by benefiting the Kalman filter method and using forgetting factor inspired by Koop and Korobilis (2014).

Pairwise directional connectedness from j to i:

$$\Phi_{ij,t}(H) = \frac{\sum_{t=1}^{H-1} \Psi_{ij,t}^{2}}{\sum_{j=1}^{m} \sum_{t=1}^{H-1} \Psi_{ij,t}^{2}}$$

note that $\sum_{j=1}^{m} \Phi_{ij,t}\,(H) = 1$ and $\sum_{i,j=1}^{m} \Phi_{ij,t}\,(H) = m$

Total connectedness index:

$$C_t(H) = \frac{\sum_{i,j=1,i\neq j}^{m} \Phi_{ij,t}\,(H)}{\sum_{i,j=1,i=j}^{m} \Phi_{ij,t}\,(H)} * 100 = \frac{\sum_{i,j=1,i\neq j}^{m} \Phi_{ij,t}\,(H)}{m} * 100$$

Total directional connectedness to others:

$$C_{i\to t,j}(H) = \frac{\sum_{j=1,i\neq j}^{m} \Phi_{ji,t}\,(H)}{\sum_{j=1}^{m} \Phi_{ji,t}\,(H)} * 100$$

Total directional connectedness from others:

$$C_{i\leftarrow t,j}(H) = \frac{\sum_{j=1,i\neq j}^{m} \Phi_{ij,t}\,(H)}{\sum_{j=1}^{m} \Phi_{ij,t}\,(H)} * 100$$

Net total directional connectedness:

$$C_{i,t} = C_{i\rightarrow t,j}(H) - C_{i\leftarrow t,j}(H)$$

Finally net pairwise directional connectedness:

$$NPDC_{i}j(H) = (\Phi_{ij,t}(H) - \Phi_{ji,t}(H))$$

if NPDC_ij(H) is positive, variable i dominates variable j.

The most important advantages of the TVP-VAR method compared to the rolling window method applied by DY are that there is no need to choose a random window size and that it avoids losing data as large as the window size. In addition, Antonakasiss et al. (2017) found that the TVP-VAR approach is less sensitive to the effects of outliers.

2.2.2.3 The Joint Spillover Index

The generalized spillover index proposed by Diebold and Yılmaz (2009, 2012, and 2014), which we discussed in detail above, is widely applied in the literature to measure connectedness. In the DY method, the connectedness measures the relative contribution of the shock that occurs in one variable to the variance of other variables in the system. However, the generalized variance decompositions approach proposed by DY does not consider the correlation between the two variables which contribute to the variance of one variable. Therefore, it will not be able to fully reflect the contribution of each variable to the change occurred in the other variable.

To solve this problem, the creation of the joint spillover index was proposed as an alternative method to measure connectedness by Lastrapes and Wiesen (2020). In this method, while the forecast error variance decomposition of each variable is calculated, the shocks in other variables are jointly addressed instead of the impact of the shock occurring in the other variable one by one.

Considering the approach in a 3-variable system X, Y and Z, if the correlation between Y and Z is positive, the DY approach, which does not take this correlation into account, will overestimate the spillover effect of Y and Z on X. As can be seen, while calculating the total spillover, the effect of the cross-correlation between two variables is ignored in the DY approach, while it is included in the equation when calculating the total joint spillover index. A three-variable example is currently being considered, and this effect becomes more complex as the number of variables becomes larger. As a result, the joint spillover index gives a more precise aggregated spillover measurement since it considers the cross-correlation between the variables. The joint spillover approach does not consider the independent effect of each variable, as in the DY approach, but the contribution of all other variables jointly.

In addition, the joint spillover connectedness approach has other additional benefits. In the DY approach, the contribution of each variable is taken, and normalization is made so that the sum of the effect of the variable on itself and the effect of all other variables in the system becomes 100%. However, since the relative contribution is considered in the joint spillover method, there is no need for such an artificial normalization.

2.2.2.4 The Extended Joint Spillover Index

While calculating the forecast error variance of a variable with the joint spillover approach, the relative contribution of each variable is taken. In other words, the correlation between other variables affecting a variable throughout the system is considered. The joint spillover connectedness approach calculates the overall connectedness of the system. While determining the total joint spillover value, the sum of the relative effect of a variable does not have to be equal to 1, since all other variables are taken as constant, and no normalization is performed.

“The TVP-VAR Extended Joint Connectedness Approach” is suggested by Balcilar et al. (2020) to overcome the main problem of this system, which is related to the calculation of the net directional connectedness value.

Lastrapes and Wiesen (2020) defined a scaling factor for the system to ensure that the net system wide spillovers are equal to zero. “The TVP-VAR Extended Joint Connectedness Approach” addresses the shortcomings in calculating the net total and pairwise directional connectedness methods by suggesting a more flexible approach where the scaling factor in the joint connectedness table is not fixed and each row has its own scaling factor.

CHAPTER 3

EMPIRICAL MODEL RESULTS

3.1 EXTREME VALUE ANALYSIS

3.1.1 Financial Time Series and Extreme Value Analysis

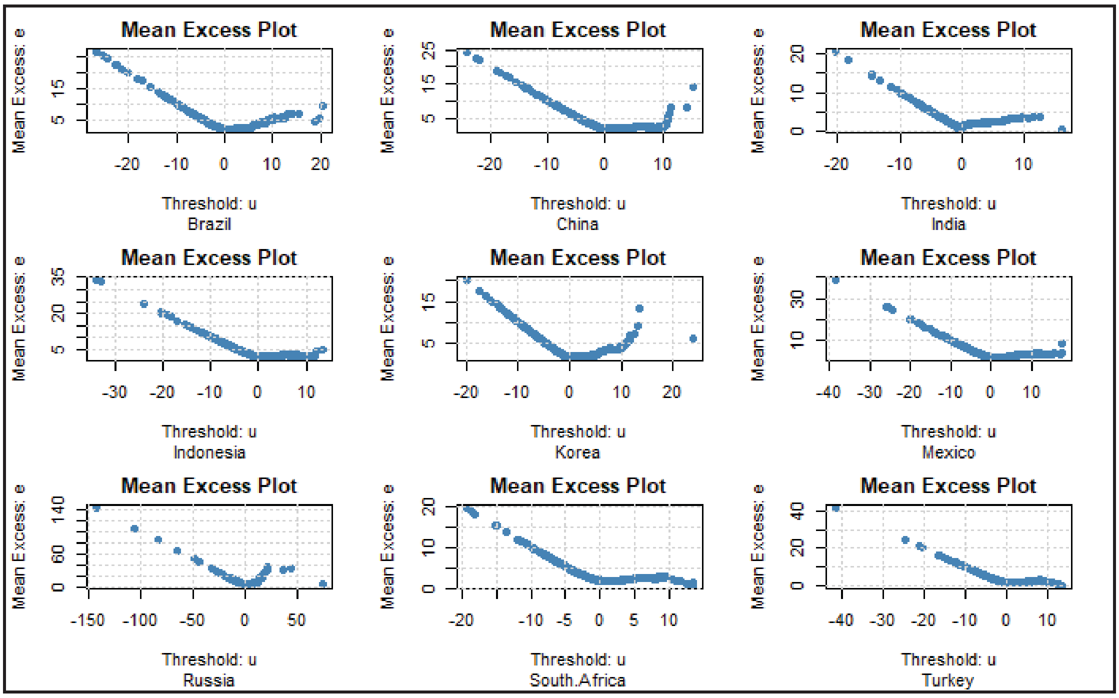
When we examine the EVT applications, it is seen that basically two methods are applied, namely Block Maxima (Minima) (BMM) and Peak Over Threshold (POT). In the BMM method, the observations are divided into blocks and the data exceeding the threshold determined in each block are taken as extreme data, and then the Generalized Extreme Value (GEV) distribution is fitted on these data. In the BMM method, it is assumed that the data are independent and identically distributed (IDD). In the POT method, all the data above a certain threshold are taken and the Generalized Pareto Distribution (GPD) is fitted. The POT method is a more efficient method of using existing data, as it receives all the data above a certain threshold. The POT method, which has been proven to be a more effective method in the literature, is used in this study.

3.1.2 Analyzing Mean Excess Plots

Finding the most suitable threshold value in an EVT application is important for the success of the application. When the threshold value is too high, too much data will be included in the analysis, but the analysis will no longer be an extreme value analysis. When the threshold value is set too low, it will be difficult to conduct an analysis with these data, since the number of data exceeding the threshold is low. In this study, the mean excess plot is used to find the threshold value (Sing and Allen, 2017).

“Mean Excess Plot” is used to find the appropriate threshold value for the POT approach. Figure 6 shows the linearity in a region where the threshold supports the GPD model from the plot. By analyzing the plot, we can indicate that the threshold value should be 10%. Although the parts where the mean excess plots are linear have a minor variation from country to country, they all became linear approximately around 10%. The EVT method is applied to both right and left tail, so it is possible to evaluate the losses and the awards. However, in this study only the left tail (extreme loses) will be taken to assess the risk of loss in the risk contagion analysis.

Figure 6: Mean Excess Plots



3.1.3 Estimation of VaR Using the Dynamic EVT-Var Method

In the implementation of the EVT approach, the GPD distribution was fit by taking the data above the threshold value, which was determined as 10 percent, as we explained above. GDP distribution parameters were estimated for the number of excess losses determined. VaR values were then calculated for the confidence interval determined using the estimated distribution. VaRq, which is frequently used in the field of risk management, is simply found by estimating the qth quantile calculated for a certain time period.

The EVT method to calculate static VaR values is described above. However, in this study, the dynamic EVT-VaR method suggested by McNeil and Frey (2000) is used. With the dynamic EVT-VaR method, the volatility in the return series is captured by applying one of the ARCH/GARCH models on the return series in the first stage. Then, using the model's residuals, the POT model is estimated in the context of the EVT. Briefly, in the first step, filtering is done using the ARCH/GARCH model and in the second step VaR values are estimated on residuals using the EVT model.

As can be seen when the return series in Figure 7 is examined, the return volatility of the sovereign CDS data shows a clustering structure. Therefore, approaches that do not consider the heteroscedasticity feature in the data will be misleading. In this thesis, the GARCH (1,1) model, whose effectiveness has been proven, is used as a volatility model. Using the GARCH model, mean and standard error for period t + 1 was estimated. The POT model was estimated by taking the residuals of the GARCH model, and the VaR estimate was made by repeating this process for each day using the one-day ahead rolling window.

It is important to determine the window size in the dynamic EVT-VaR approach. Within the scope of the EVT model, since the extreme values exceeding the threshold for the window size are predicted, the prediction model does not work or does not give effective results when the window size is too small. When the size of the window is too large, the data loss rate is very high. In this study, the window size was taken as 1000, and similar results were obtained when different window sizes were tried by performing a robustness analysis. As a result, 1 percent VaR values were estimated using the R codes in the dynamic EVT-VaR model, Sign and Allen (2017) Chapter 10. Dynamic EVT-VaR series are calculated by applying the GARCH (1,1) method in filtering the sovereign CDS series and then the GPD method is applied to the residuals. The steps of the calculation are summarized below (Singh and Allen (2017):

- GARCH (1,1) model is applied to the sovereign CDS return data.

- GARCH (1,1) model is used to estimate mean and standard error for period t + 1.

- Residuals of the GARCH (1,1) model are taken.

- 90% for residuals and over POT are applied to residuals/ 10% threshold is chosen/Negatives are taken for the left tail.

- Fit the GPD using the EVT theory for 99% probability.

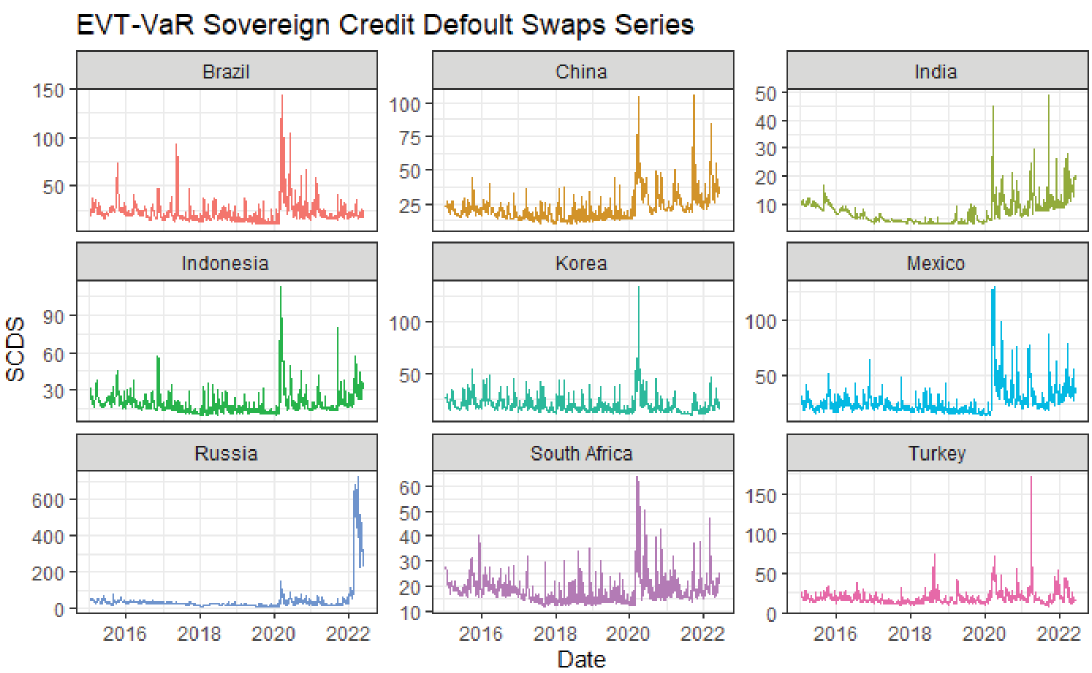
- Estimate 1% dynamic EVT VaR using the formula below:

$VaR_q = m_{t+1} + s_{t+1}\ VaR(Z_q)$

-Repeat the same steps for one-day ahead rolling window.

We obtained the dynamic EVT-VaR series for each emerging country by applying the steps mentioned above and these series are shown in Figure 7. When we examine these series, it is seen that there are sudden increases and decreases due to both country-specific and global reasons. In the following sections of this thesis, the connectedness analysis will be performed using the EVT-VaR series we have obtained as an extreme risk measure.

Figure 7: EVT-VaR Series for Sovereign Credit Default Swaps of BRICS and MIST Countries



All the extreme risks were affected by the European debt crisis, even if the rising times of risks were different. The increased risk perception about the payment of government debt in the European Union countries led to the questioning of the debt payment capacity of emerging countries. As a result, there has been a significant increase in the spreads of SCDS that have received a deficit risk of the country's treasury bond market.

In recent years, one of the most important reasons that have increased the extreme risk values of countries is the COVID-19 pandemic. As can be seen in the figure 7, a large leap is observed in the calculated EVT-VaR values of all countries. Especially in developing countries, the burden brought on the health system by the COVID-19 pandemic and the expenditures made for this reason caused a serious increase in the country's budgets, leading to a risk in the sustainability of the financial system. At the same time, the decrease in economic activities due to the Covid-19 pandemic measures caused a decrease in the government's tax revenues and led to the deterioration of fiscal balances.

In addition, the Russia-Ukraine war caused the Sovereign CDS values in these countries to rise excessively and led to the deepening of the already existing financial problems such as the energy and food crisis for all emerging countries. Russia's CDS values have reached record levels, and the crisis has led to an increase in extreme risks in other countries.

Although, global events explain the major fluctuations, country-specific events that threaten the stability of the countries have also a significant effect on sovereign CDS. It is observed that countries’ extreme risks increase especially during periods of change of political power and political instability, such as election periods, but most of them do not affect other countries and remain country specific.

3.2 CONNECTEDNESS ANALYSIS

After the GFC, studies dealing with the spillover effects of the crises have increased considerably. It is observed that the recurrent crises over the years show similar characteristics. In times of crisis, volatility and total spillover in financial assets raised considerably. For this reason, the increase in the total spillover in the market is a crisis indicator and serves as an early warning mechanism.

The connectedness model developed by Diebold and Yılmaz (2009, 2012 and 2014) is widely used to perform spillover analyses. The original model of connectedness has been improved in many ways over time. In this study, the TVP-VAR Extended Joint Connectedness Analysis is applied on risk metrics obtained using the Dynamic EVT-VaR method to find extreme risk connectedness.

The R package ConnectednessApproach (2022) was used to create tables and figures in the analyses in this thesis. The forecast horizon was selected as 20 days. In addition, the Schwarz information criterion was used to select the optimal lag order. Based on the Phillips-Perron unit root and Augmented Dickey-Fuller tests, there is no unit root at the 5% confidence interval for EVT-VaR sovereign CDS and return series.

3.2.1 Averaged Connectedness Analysis

Table 2 shows the average total connectedness values calculated for the EVT-VaR sovereign credit default swap network for all countries using the TVP-VAR extended joint connectedness method. In the table, each row displays the contribution of the shock from each country to the forecast error variances of the other country (to others). Each column indicates the contribution of other countries to the forecast error variance of each country (from others). While the diagonal elements in the table display their own contribution, the remaining off-diagonal elements indicate the values of "to others" or "from others".

When Table 2, presenting EVT-VaR sovereign credit default swaps, is analyzed, the averaged joint connectedness index is 65.25. In other words, 65.25% of the forecast error variance explained by the other countries’ sovereign CDS risk measures. This study shows that the market risk for sovereign CDSs is quite high.

In the table, a net positive value means that shocks occurring in that country affect other countries more than they receive, while countries that have negative values are net shock receivers. When the average total connectedness values in Table 2 are investigated, Russia, South Korea, India, Mexico, and South Africa are net transmitters of the shocks, while Türkiye, Indonesia, China, and Brazil are net receivers of shocks. While the highest shock receiver countries are Türkiye, Indonesia, and China, in descending order, Russia dominantly has the highest share among shock transmitting countries.

Table 2: Averaged Joint Connectedness Table for EVT-VaR Sovereign CDS Data of BRICS and MIST Countries

	Brazil	China	India	Indonesia	Korea	Mexico	Russia	South Africa	Turkey	FROM
Brazil	31.45	6.93	4.02	8.71	7.22	20.01	8.93	8.11	4.63	68.55
China	7.03	19.78	7.83	15.52	13.96	11.59	12.44	7.27	4.58	80.22
India	4.85	8.26	41.49	7.43	4.24	8.92	15.91	4.64	4.26	58.51
Indonesia	9.04	15.40	6.25	18.85	13.23	12.58	12.47	7.78	4.41	81.15
Korea	6.51	15.89	4.80	15.93	25.95	8.53	13.09	5.62	3.68	74.05
Mexico	17.21	9.37	4.82	9.06	6.47	27.25	11.21	8.72	5.89	72.75
Russia	2.77	4.01	7.13	3.09	1.65	6.41	68.06	4.08	2.80	31.94
South Africa	9.32	7.01	4.04	8.14	5.41	12.08	14.20	30.92	8.88	69.08
Turkey	6.05	5.53	3.12	6.13	3.65	8.51	8.68	9.33	48.99	51.01
TO	62.79	72.40	42.01	74.01	55.83	88.63	96.92	55.54	39.13	587.25
Inc.Own	94.24	92.18	83.50	92.87	81.78	115.88	164.98	86.46	88.12	TCI
NET	-5.76	-7.82	-16.50	-7.13	-18.22	15.88	64.98	-13.54	-11.88	65.25
NPT	5.00	3.00	1.00	5.00	1.00	7.00	8.00	4.00	2.00	

We calculated the average total connectedness values for the Sovereign Credit Default Swap return series, with the Extended Joint Connectedness method, and the results are included in Table 3. For the Sovereign CDS return series, the averaged joint connectedness index is 64.35, which is lower than the EVT-VaR results.

When the average total connectedness values in Table 3 are considered, Brazil, China, South Korea, Mexico, Russia, and South Africa are net transmitters of the shocks, while India, Indonesia and Türkiye are the net receiver of shocks. China, Mexico, and South Korea have the highest share among shock transmitting countries, in descending order, while the highest shock receiving countries are India and Indonesia, in descending order.

When we compare the results of the extended connectedness analysis with EVT-VaR and sovereign CDS return series, it is seen that the average net shock recipient and transmitter status of countries and the average effects of shocks are different from each other.

Table 3: Averaged Joint Connectedness Table for Sovereign CDS Return Data of BRICS and MIST Countries

	Brazil	China	India	Indonesia	Korea	Mexico	Russia	South Africa	Turkey	FROM
Brazil	32.83	4.68	1.96	5.66	4.51	22.70	7.92	12.05	7.68	67.17
China	7.80	21.45	5.55	20.45	18.28	8.79	5.50	7.53	4.64	78.55
India	3.53	6.02	64.33	8.31	5.60	4.32	2.92	3.05	1.93	35.67
Indonesia	9.42	17.71	6.37	18.46	15.16	10.63	6.82	9.22	6.21	81.54
Korea	7.03	18.54	4.91	17.51	27.32	8.20	5.22	6.75	4.51	72.68
Mexico	22.13	4.92	2.37	6.17	5.05	29.89	8.81	12.73	7.94	70.11
Russia	7.44	3.42	1.68	4.96	3.45	8.41	51.48	11.00	8.16	48.52
South Africa	11.38	5.40	2.04	7.43	4.94	12.16	10.93	31.17	14.56	68.83
Turkey	8.45	3.89	1.47	5.32	3.61	8.67	8.82	15.82	43.94	56.06
TO	77.17	64.57	26.35	75.81	60.61	83.88	56.96	78.15	55.63	579.13
Inc.Own	110.00	86.03	90.68	94.27	87.93	113.77	108.43	109.32	99.57	TCI
NET	10.00	-13.97	-9.32	-5.73	-12.07	13.77	8.43	9.32	-0.43	64.35
NPT	5.00	2.00	0.00	3.00	1.00	6.00	7.00	8.00	4.00	

3.2.2 Averaged Dynamic Total Connectedness

With the connectedness approach, it is possible to see the pattern of how all the variables in the system are affected by a random shock. The total connectedness index (TCI) is called systemic risk or market risk because it shows the average of the effects of shocks that occur in one country to all other countries in the network, but it is not a time varying value.

In Figure 8, which shows the dynamic total connectedness, it is observed that the connectedness effect is quite high during crisis periods. This indicates that the herding effect is high in sovereign CDS pricing during the crisis. High connectedness during the recession periods also means that the advantage of the diversification opportunity for investors is reduced considerably.

The changes in the total connectedness value have hovered between 70% and 80% throughout 2015 and 2016. While developed countries achieved a recovery and relatively rapid growth after the global financial crisis and the following debt crises, developing countries showed a relatively slow growth. Geopolitical tensions between Russia and Ukraine and economic sanctions imposed on Russia have negatively affected both Russia and the emerging market economies with the strong spillover effect (International Monetary Fund, 2015).

As of 2015, foreign direct investments in Russia have dropped dramatically, growth and the value of the ruble have decreased. At the same time, the record low oil price level in 2015 led to the deterioration of the financial structures of Russia and the other oil exporting countries. Sovereign CDS values have rapidly increased because of the risks related to fiscal sustainability. The sharp decline in oil price, increasing inflation, and rapidly increasing government expenditures had a serious negative impact also on the Brazilian economy directly.

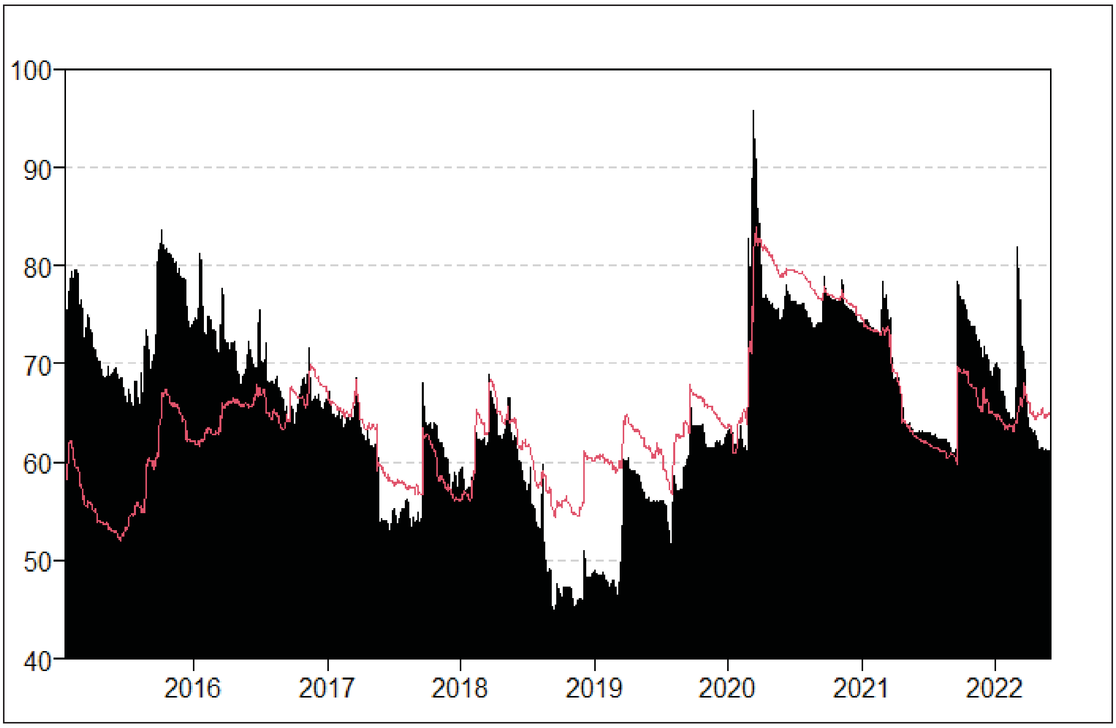
The value of total connectedness, which started to decrease gradually after 2016, reaches its lowest level in 2019. As the COVID 19 epidemic caused the sovereign CDS values of all countries to jump, the total connectedness value reached a record level of over 90% in 2020. The uncertainty brought about by the COVID 19 pandemic and the high increase in health expenditures have brought along the fear of the sustainability of the financial structures of emerging countries. Disruptions in the production chain and increasing unemployment have led governments to increase the social benefits for citizens in all countries, causing budget deficits to increase.

In 2022, while the economic effects of the Covid 19 pandemic are decreasing in all countries, problems in China have sustained because of the local lockdown practices due to the zero-case policy. Due to the Russian war in Ukraine and international sanctions, many emerging countries are experiencing sharp declines in economic growth. In addition, the food and energy crises that have arisen and the social relief policies implemented by governments in order not to reflect high energy prices on citizens put a burden on the government budgets, threatening the continuation of financial sustainability. Also, in many countries, anti-inflation policies continue to be implemented.

As of the end of 2022, the major problem especially in developing countries is the strong dollar value along with the food and energy crisis. Due to the FED's successive interest rate hikes in the recent period, the dollar has risen considerably against all currencies, particularly against emerging market currencies.

The strength of the dollar affects developing countries in many ways. The high value of the dollar primarily causes the imported products to be expensive for other countries. It leads to an increase in the debt burden of emerging market countries, which borrow especially with dollar dominated debt securities, increasing the share of borrowing rate in the budget. Since the depreciation of the country's currency against the dollar causes the value of tax revenues to decrease, problems arise in paying foreign debt obligations. For this reason, even though the impact of the economic consequences due to the Covid 19 pandemic has decreased, the financial sustainability problem of emerging countries continues. Finally, Russia's potential retaliation also causes the uncertainty to increase.

Figure 8 : Averaged Dynamic Total Connectedness of BRICS and MIST Countries



3.3 NET DYNAMIC TOTAL CONNECTEDNESS

During and after financial crises, countries' risk of bankruptcy increases significantly. A country's financial sustainability problem also directly affects the credit risk of other countries. Financial structures of emerging countries are closely interconnected through many channels. When a country's risk of bankruptcy increases, CDS premiums increase both for the country in question and for other emerging markets with similar financial structures, thus increasing a systemic risk.

Figure 8 provides information about net dynamic connectedness of EVT-VaR series for BRICS and MIST countries. The net dynamic total connectedness value is found by subtracting “the total directional connectedness from others” data (Figure 10) from “the total directional connectedness to others” data (Figure 9) for each country's EVT-VaR value. The net dynamic connectedness value's being positive indicates that the impact of a shock in that country to all countries is greater than the impact of a shock that occurred in all other countries to this country. EVT-VaR connectedness results in Figure 8 are presented in black, while sovereign CDS return results are shown with a red line for comparison.

Analyzing Figure 8, it is noteworthy that Russia was the main transmitter of shock throughout the entire time interval. Based on the BRICS and MIST countries, it is observed that Russia is the most important determinant of the level of connectedness. Mexico is observed to be one of the most important net transmitters of shocks in 2017-2018 and after 2020. South Korea, South Africa, and Türkiye appear to be the main receiver of shocks throughout, with very exceptional few periods.

Figure 9: Net Dynamic Total Connectedness of BRICS and MIST Countries

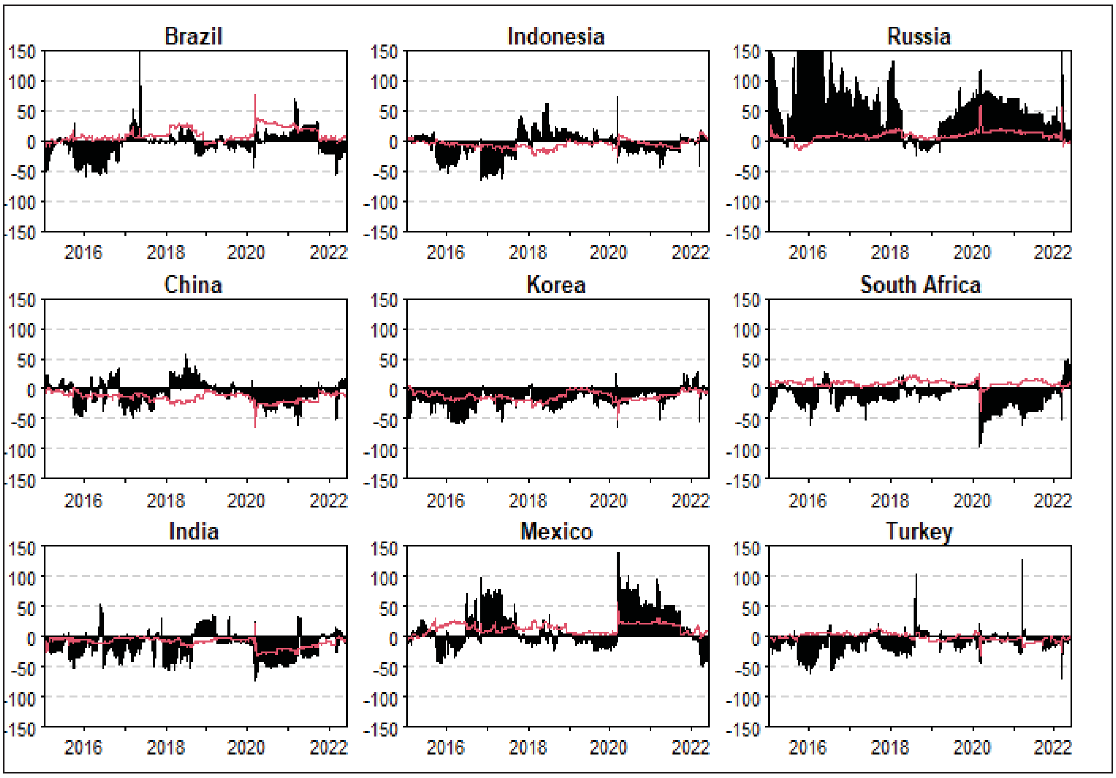


Figure 10 shows the dynamic total connectedness to others data. In other words, the change occurs over time regarding the state of each country's being a total shock transmitter or receiver. The results obtained using the EVT-VaR data, which is the main purpose of this study, are presented with the black area, while the results obtained from the log return sovereign CDS return data are shown with a red line for comparison. As a general assessment, it is seen that extreme risk spillover values are much more responsive to extreme events when compared to return series results. For this reason, it is possible to analyze the changes in the connectedness structure in a more detailed way over time with extreme risk spillovers.

"To connectedness" data shows significant changes over time, as it is directly affected by the changes that occur within a country. The country's risk transfer rate is increasing because of the political environment, elections, economic stability, and debt sustainability issues. In the total dynamic connectedness to others graph in Figure 9, it is seen that "the directional spillover to others" of each country changes over time; in other words, it is time varying. Especially in Brazil, Russia, and Mexico, it is seen that "to others" values vary a lot over the years. In Figure 10, the values of "total dynamic connectedness from others" are included, and these values differ from country to country. For example, Russia with a very high "to others" values has the lowest "from others" quantity, so a shock in other countries has a very low impact on Russia.

Figure 10: Total Dynamic Connectedness to Others of BRICS and MIST Countries

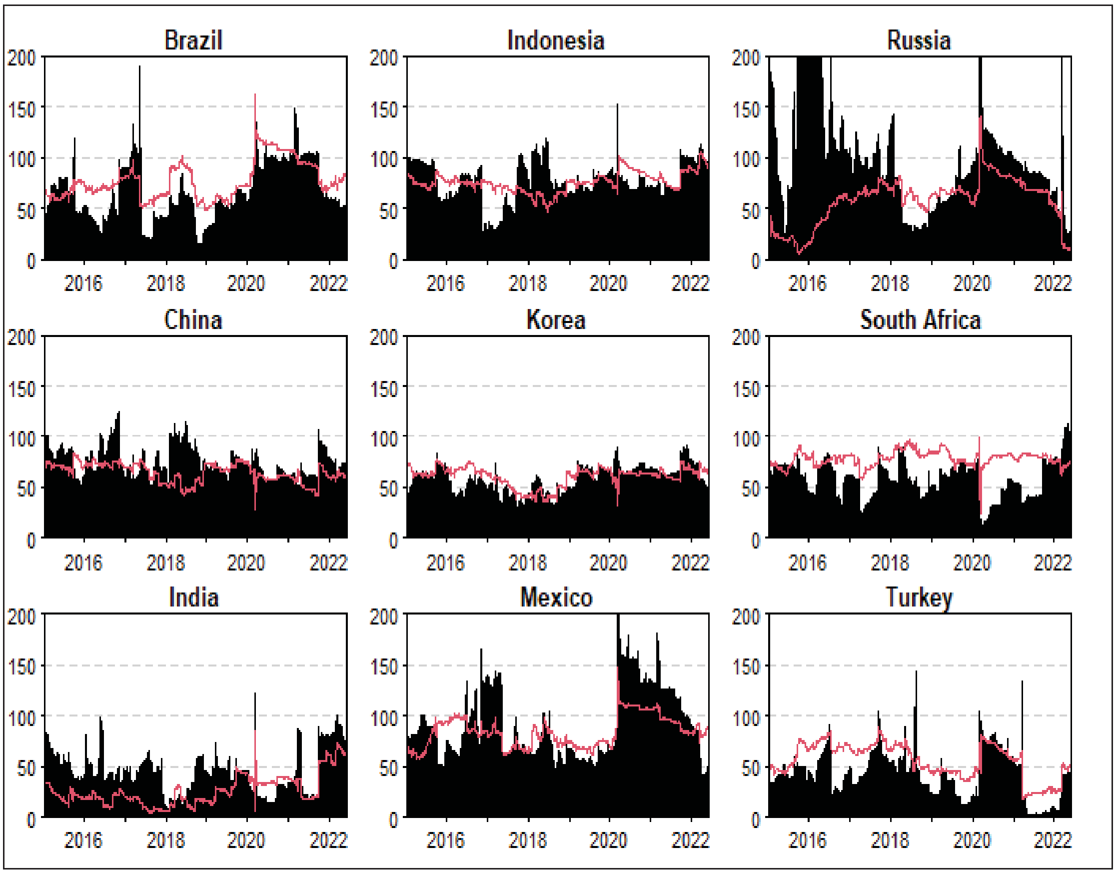
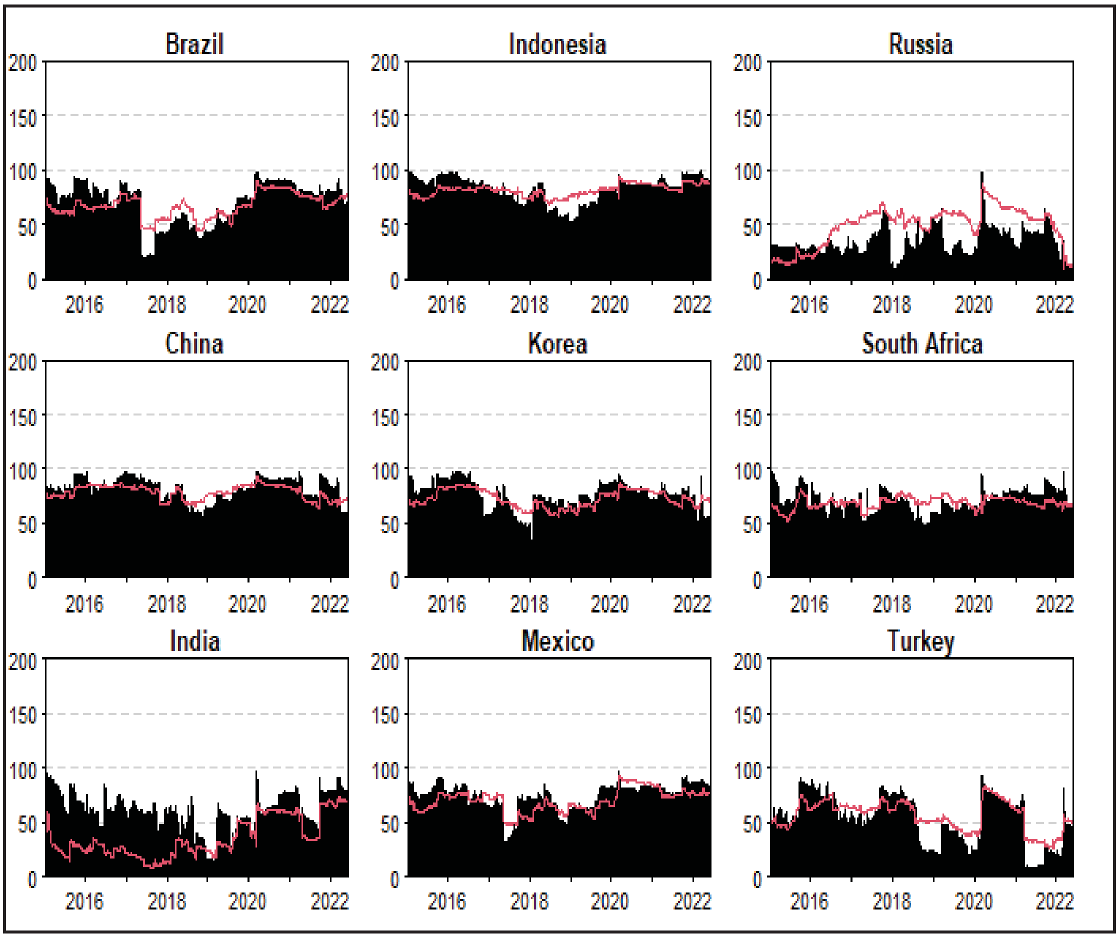


Figure 11: Total Dynamic Connectedness from Others of BRICS and MIST Countries



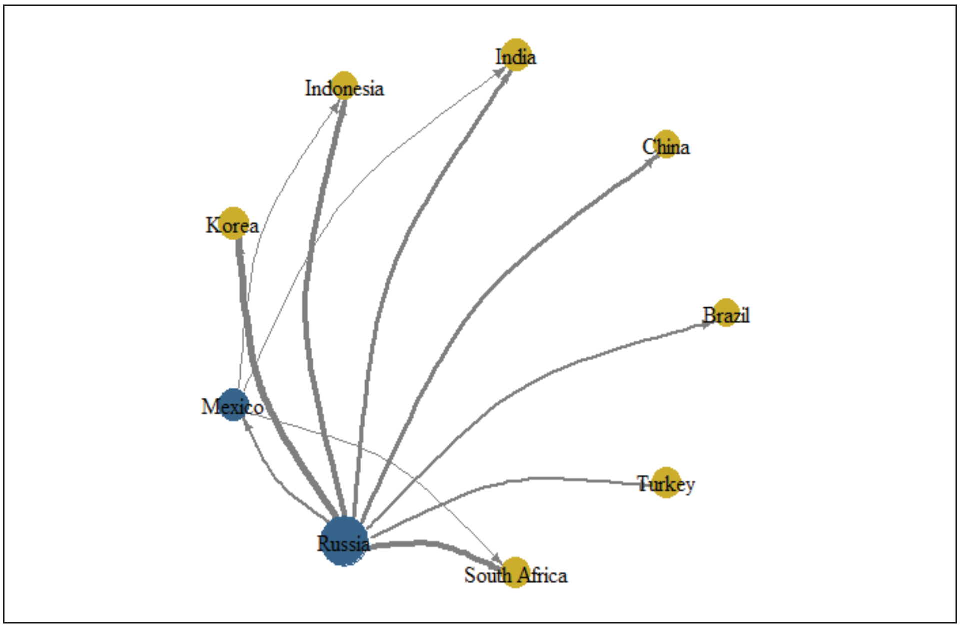
3.4 DYNAMIC PAIRWISE CONNECTEDNESS

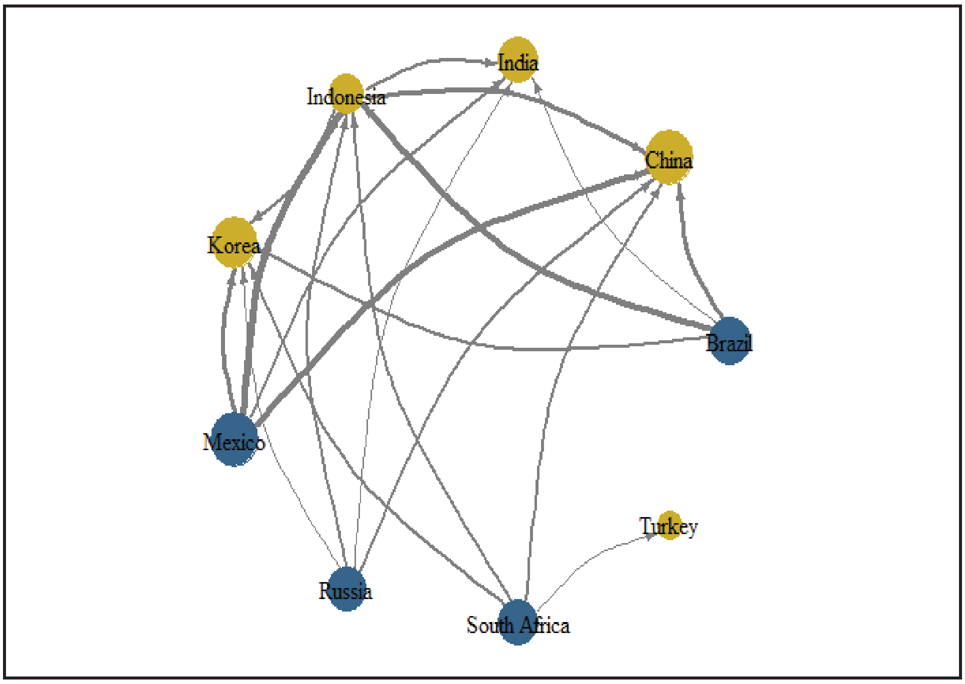
3.4.1 Dynamic Net Pairwise Connectedness Plots

Dynamic net pairwise connectedness was analyzed via network analysis in Figure 12. Russia has a central role in shock transmitting of extreme risks, affecting all countries. Mexico follows Russia as the net shock transmitter of shocks. On the other hand, in the second network graph, the log return sovereign CDS connectedness results do not reflect the dominant role of Russia as a net shock transmitter.

Analysis of the return sovereign CDS network in Figure 12 proved that Türkiye is not strongly interconnected with other economies. Türkiye, which was only affected by a shock in South Africa sovereign CDS to a limited extent as a shock recipient, stands apart from other countries. As a result of limited interconnectedness, Türkiye was affected less by systematic risks. On the other hand, Türkiye has a high level and volatile sovereign CDS values, which means that the country's high-risk perception stems from events occurring within the country itself, rather than external factors.

Figure 12: Dynamic Net Pairwise Connectedness Plots for EVT-VaR and Return Series of BRICS and MIST Countries





3.4.2 Dynamic Total Pairwise Connectedness Plots

The dynamic total pairwise connectedness graph in Figure 13 shows the change in pairwise connectedness between two countries over time. The highest bilateral relationships observed are Brazil-Mexico, China-Indonesia, Indonesia-South Korea, and China-South Korea pairs. This situation reveals the importance of geographical location in connectedness between country pairs. The fact that the clustering structure of connectedness is mainly determined by the geographical location is compatible with the current literature (Diebold and Yilmaz, 2015 and Bostanci and Yilmaz, 2015).

One of the reasons for the increase in extreme risk connectedness in emerging markets is that the managers of international funds, which have increased rapidly in recent years, make their portfolio allocation decisions based on the clustering structure of emerging countries. Portfolio allocation decisions of large-scale international funds lead to an increase in emerging market connectedness in extreme market conditions. Emerging market financial markets become more vulnerable to extreme risks as a result of capital inflow and outflow behaviors that occur as a result of the investment behaviors of these funds. After the 2008 global financial crisis, asset investments in emerging markets increased significantly. Due to the continuously low interest rates in developed countries, fund investors have turned to emerging market economies to obtain high returns.

Asset managers play an important role in financial markets, especially following a global financial crisis. The MSCI EM Index is the most important guiding factor for investments in developing countries. The MSCI EM index, which was created in 1988 and consisted of 10 countries with a weight of about 0.9% in 1988, consists of 24 emerging countries today and constitutes 12% of the MSCI ACWI. This index includes 85% of the free float-adjusted market capitalization in each country. As of January 2023, China takes the first place in country weights with 33%, followed by Taiwan with 14.42% and India with 12.97% (The MSCI Emerging Markets Index Factsheet, 2023).

In recent years, most of the investments have been made by large-scale index funds. This large investment industry is dominated by a limited number of index providers.

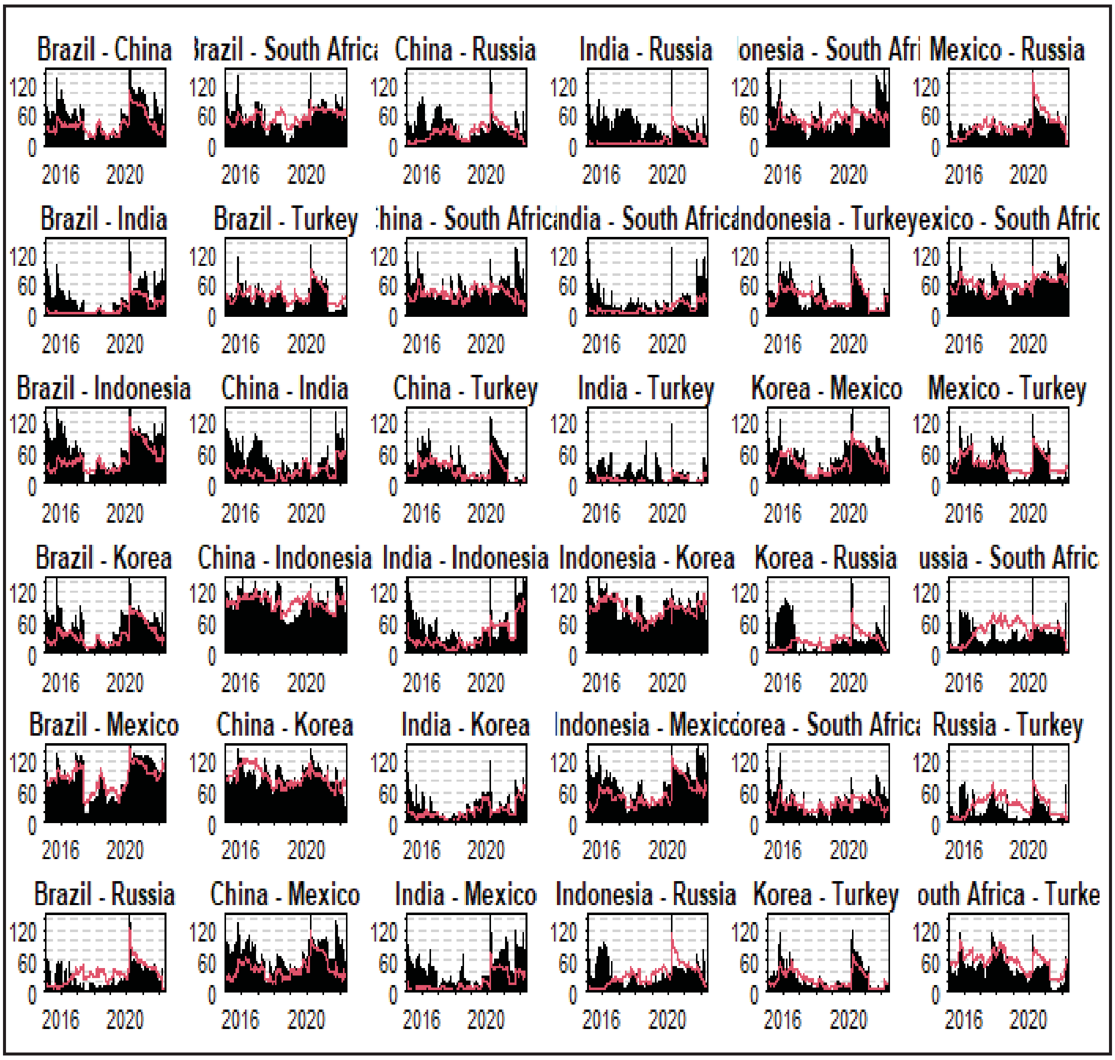
Through index classifications and country weights, these asset managers significantly determine the capital flows to a country. The MSCI classifies countries according to three criteria, namely economic development, size and liquidity, and market accessibility for foreign investors. Many other investors also invest based on this classification and country weights. For this reason, the reclassification of countries causes very rapid inflow of funds to and outflow of funds from developing countries. Index providers thus become the decision makers as to which countries are worth to invest (Petry et all, 2021).

Asset managers basically carry out fund management in two ways, active and passive management. While active funds are not tied to a particular benchmark index, passive funds either apply or closely follow the benchmark index. As a result of the widespread use of the benchmark-driven index, the correlation between investments increases. Emerging markets are becoming more risk sensitive as there are too many asset investors and emerging markets are relatively less liquid. Miyajima and Shim (2014) proved in their study that firstly, active funds also follow benchmark indexes closely, and secondly, investment flows to emerging markets cause cyclical instability. As a result of the use of the same or similar benchmarks by both active and passive funds, a comovement occurs among final investor behaviors. This situation causes an increase in the correlation between investments in emerging countries.

Many studies have suggested that the investment behavior of fund managers investing in emerging markets is one of the possible reasons for the rapid increase in connectedness in these markets. A study on capital flows to Emerging markets by Lau et al. (2019) found that Benchmark-driven investments increase connectivity between emerging markets. One reason for this increase in connectivity is that Benchmark-driven fund managers perceive all emerging markets as a single asset class. Especially in stressful financial conditions, when foreign investors decide to reduce their investments in emerging markets, all emerging markets are affected together, and all these countries experience financial problems. Lau et al. (2019) showed that this connectivity increase cannot be attributed to geographical reasons alone and that even among countries with very low geographical, economic, and commercial ties, the correlation is very high due to benchmark-driven investments. In short, emerging markets are exposed to similar risks due to the behavior of fund investors, and the connectedness between them rises regardless of geographical or economic reasons.

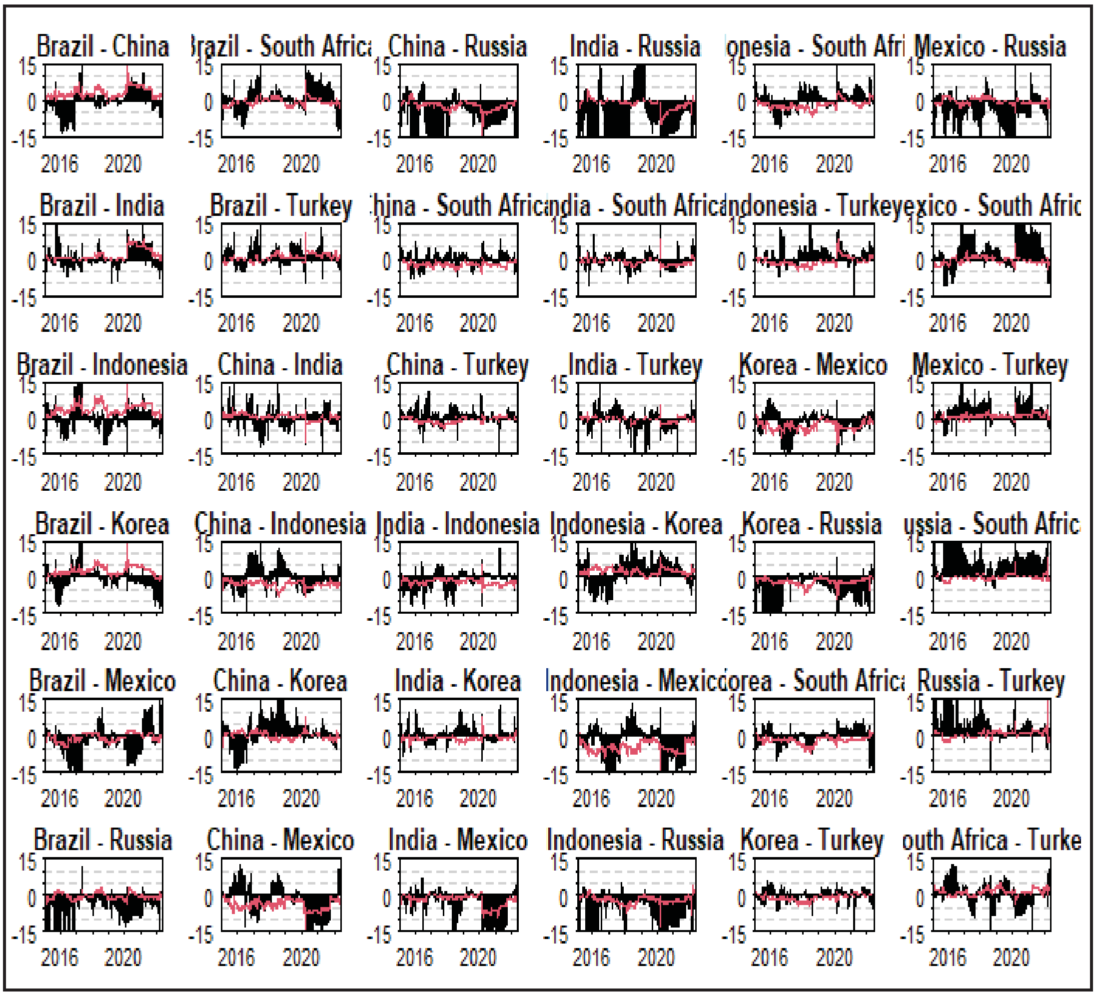
The rapid growth of benchmark-driven investments over time has resulted in a very high ratio of these funds to total investments in emerging markets. The portfolio allocation behavior between countries in benchmark-driven mutual funds is determined by the weights of the countries in these funds. As shown above, non-index-based active funds also closely monitor the country weights of these Benchmark-driven funds. Benchmark-driven funds are very sensitive to global factors and consider all emerging market investments as a single asset class; in other words, they evaluate emerging market economies as a single group. Therefore, investment decisions are made based on global factors, and country-specific factors such as a country's economic fundamentals are not considered (IMF, 2019). As a result, since benchmark-driven funds make decisions according to common factors for all emerging markets, rapid fund flows, especially in extreme risk market conditions, cause an increase in connectedness among emerging markets.

Figure 13: Dynamic Total Pairwise Connectedness Plots of BRICS and MIST Countries



When dynamic net pairwise connectedness in Figure 14 is examined, it is seen that Russia is a high net shock transmitter to other countries in pairwise connectedness. Following Russia, Mexico has a strong influence as a net shock transmitter after 2020.

Figure 14: Dynamic Net Pairwise Connectedness Plots of BRICS and MIST Countries



3.5 EVT-VAR EXTENDED JOINT CONNECTEDNESS ANALYSIS OF BRICS AND MIST COUNTRIES WITH S&P 500 AND MSCI EM INDICES

In this section, sovereign CDS values of BRICS and MIST countries as well as S&P 500 and MSCI EM indices are included in the extended joint connectedness calculation conducted with EVT-VaR return series. EVT-VaR series is calculated by applying dynamic extreme value theorem for S&P 500 and MSCI EM indices as well as for sovereign CDS series. As seen in Table 4, when the S&P 500 and MSCI EM indices are added to the model, the net spillover index realized by Russia to other countries increased from 64.98 to 69.40. While the MSCI EM index, which consists of the stocks selected from the emerging market stock markets, is a net shock receiver with a high amount from the BRICS and MIST countries in terms of extreme risk spillover, the S&P 500 index is a net shock transmitter.

When the return connectedness values in Table 5 are considered, it is seen that both S&P 500 and MSCI EM indices are net shock transmitters, but S&P 500 index creates a stronger spillover effect. Figure 15, which demonstrates averaged dynamic total connectedness of BRICS and MIST countries with S&P 500 and MSCI EM Indices, has the similar pattern with Figure 8, which shows the results with only BRICS and MIST countries. In addition, when Figures 16 and 17 are analyzed, it is seen that the S&P 500 and MSCI EM indices interact with each other the most, rather than the countries' sovereign CDSs, and the spillover effect is from the S&P index to MSCI EM index.

Table 4: Averaged Joint Connectedness Table for EVT-VaR Sovereign CDS Data of BRICS and MIST Countries with S&P 500 and MSCI EM Indices

	Brazil	**China**	**India**	**Indonesia**	**Korea**	**Mexico**	**Russia**	**South Africa**	**Turkey**	**S&P 500**	**MSCI EM**	**FROM**
Brazil	30.46	5.60	3.22	7.14	6.25	17.58	7.21	7.90	4.12	5.91	4.60	69.54
China	6.53	17.39	6.54	14.34	12.80	9.36	9.31	6.73	3.94	6.40	6.66	82.61
India	5.02	6.68	38.71	6.87	3.60	7.55	13.52	3.89	3.75	5.51	4.92	61.29
Indonesia	8.40	14.01	5.18	17.46	12.07	10.32	10.88	7.25	3.85	4.52	6.06	82.54
Korea	6.13	14.65	3.95	14.43	24.55	6.76	12.27	5.30	3.38	3.31	5.26	75.45
Mexico	16.25	7.47	3.81	7.51	5.36	23.40	9.46	8.28	5.03	8.07	5.36	76.60
Russia	3.10	3.45	5.46	3.53	1.72	6.34	62.51	4.01	2.83	3.18	3.86	37.49
South Africa	9.32	6.08	3.35	7.46	4.84	11.25	12.87	30.21	7.92	3.20	3.51	69.79
Turkey	5.82	4.85	2.44	5.95	3.29	7.00	7.11	8.78	47.33	3.66	3.77	52.67
S&P 500	5.71	4.85	6.18	4.72	3.20	6.26	13.62	2.98	2.30	40.54	9.62	59.46
MSCI EM	6.83	5.68	4.47	5.97	5.15	6.26	10.63	4.50	3.17	15.99	31.35	68.65
TO	73.11	73.32	44.59	77.92	58.29	88.68	106.89	59.63	40.30	59.73	53.61	736.07
Inc.Own	103.57	90.72	83.30	95.38	82.84	112.08	169.40	89.84	87.63	100.28	84.96	TCI
NET	3.57	-9.28	-16.70	-4.62	-17.16	12.08	69.40	-10.16	-12.37	0.28	-15.04	66.92
NPT	6.00	3.00	2.00	6.00	1.00	8.00	10.00	5.00	2.00	7.00	5.00	

Table 5: Averaged Joint Connectedness Table for Sovereign CDS Return Data of BRICS and MIST Countries with S&P 500 and MSCI EM Indices

	Brazil	China	India	Indonesia	Korea	Mexico	Russia	South Africa	Turkey	S&P 500	MSCI EM	FROM
Brazil	31.46	3.96	1.63	4.58	3.82	18.87	6.59	9.94	6.40	7.06	5.68	68.54
China	6.87	20.40	4.53	17.09	14.99	7.72	4.71	6.67	4.12	6.38	6.53	79.60
India	3.18	5.40	62.82	7.34	5.06	3.77	2.56	2.91	1.88	2.56	2.52	37.18
Indonesia	8.16	14.85	5.23	17.55	12.62	9.18	5.79	8.02	5.43	6.53	6.65	82.45
Korea	6.12	15.18	4.04	14.49	25.75	7.22	4.48	5.98	3.99	6.56	6.20	74.25
Mexico	18.52	4.32	1.99	5.23	4.47	27.15	7.49	10.69	6.76	8.29	5.08	72.85
Russia	6.59	2.92	1.48	4.17	2.93	7.48	50.57	9.67	7.17	3.12	3.89	49.43
South Africa	9.65	4.65	1.72	6.19	4.23	10.37	9.29	29.74	12.39	4.75	7.02	70.26
Turkey	7.21	3.40	1.27	4.51	3.16	7.51	7.60	13.56	43.31	3.37	5.09	56.69
S&P 500	7.59	2.38	0.93	2.84	2.64	9.18	3.24	5.29	3.30	54.65	7.97	45.35
MSCI EM	7.00	4.88	1.39	5.64	4.77	6.46	4.32	7.50	5.14	9.04	43.86	56.14
TO	80.89	61.95	24.22	72.07	58.69	87.75	56.07	80.24	56.59	57.66	56.62	692.75
Inc.Own	112.36	82.35	87.03	89.62	84.44	114.89	106.64	109.98	99.90	112.31	100.48	TCI
NET	12.36	-17.65	-12.97	-10.38	-15.56	14.89	6.64	9.98	-0.10	12.31	0.48	62.98
NPT	7.00	2.00	0.00	3.00	1.00	8.00	9.00	10.00	5.00	6.00	4.00	

Figure 15: Averaged Dynamic Total Connectedness of BRICS and MIST Countries with S&P 500 and MSCI EM Indices

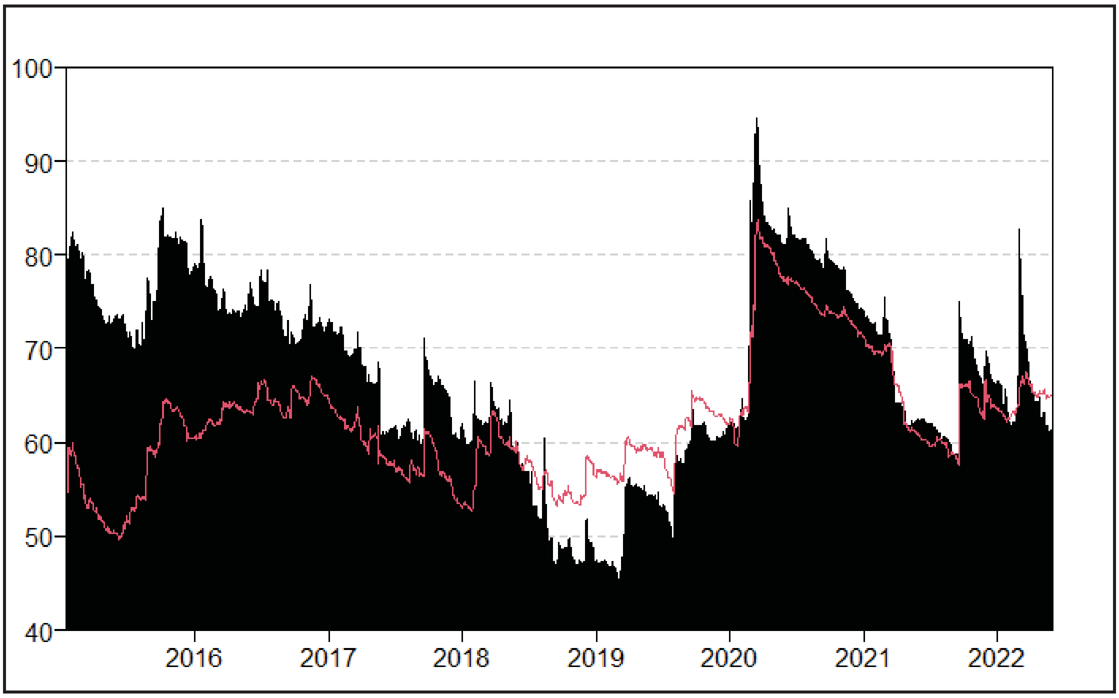


Figure 16: Net Dynamic Total Connectedness of BRICS and MIST Countries with S&P 500 and MSCI EM Indices

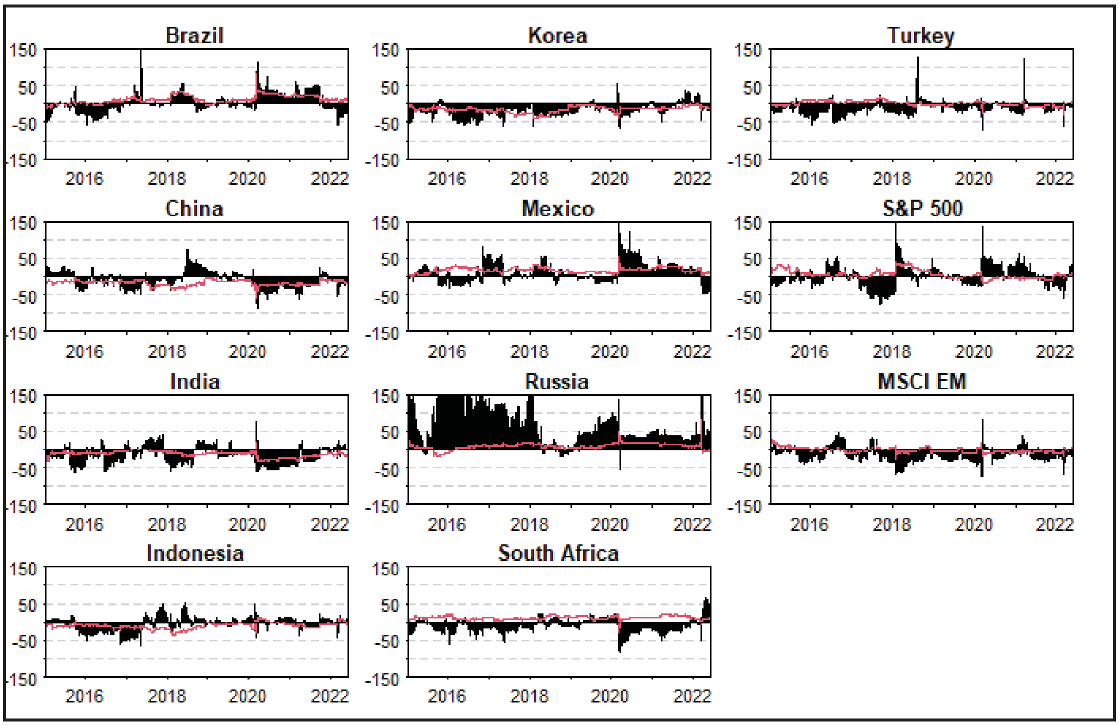
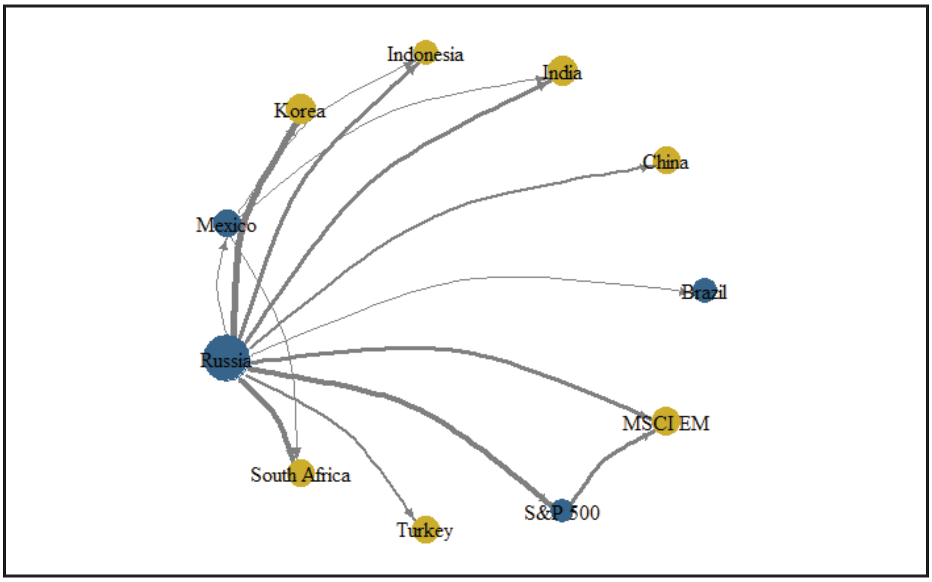
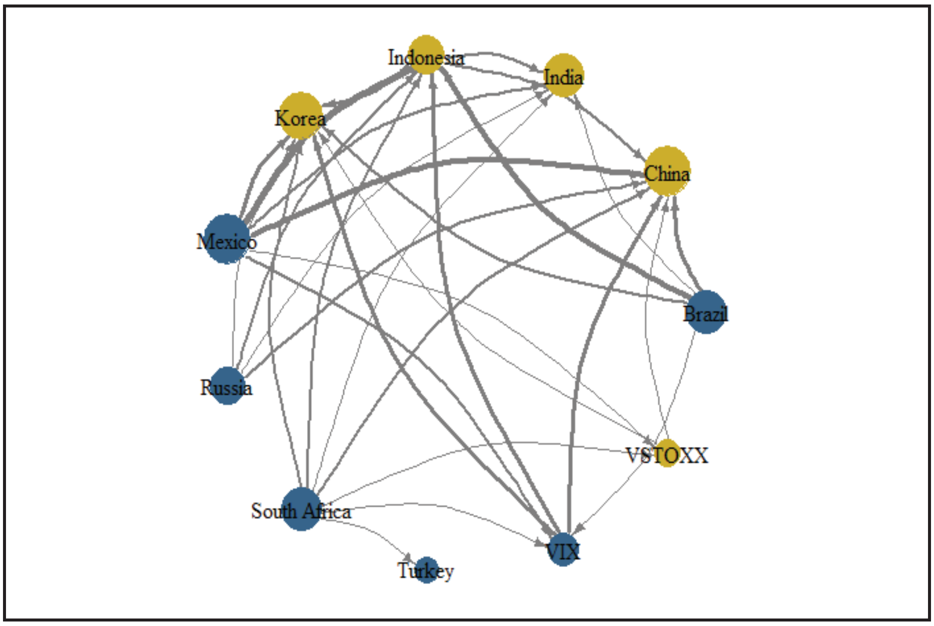


Figure 17: Dynamic Net Pairwise Connectedness Plots for EVT-VaR and Return Series of BRICS and MIST Countries with S&P 500 and MSCI EM Indices





3.6 EVT- EVT-VAR EXTENDED JOINT CONNECTEDNESS ANALYSIS OF BRICS AND MIST COUNTRIES WITH VIX AND VSTOXX INDICES

In this section, while calculating extreme risk connectedness, volatility indices, the VIX and the VSTOXX are added to the model, as well as sovereign CDS values of BRICS and MIST countries. EVT-VaR values were calculated also for VIX and VSTOXX data by applying the Dynamic Extreme Value theorem. When the data in Table 6 are examined, it is seen that VIX and VSTOXX Indices are mostly connected with each other rather than sovereign CDS data and the direction of the spillover effect is from VIX index to VSTOXX Index. Considering the return connectedness data in Table 8, VIX index is the net shock transmitter while VSTOXX Index is the net shock receiver. When Figures 19 and 20 are examined, one of the most remarkable issues is that the spillover effect from Russia on the VSTOXX index is much higher than the VIX index. It shows that extreme events that took place in Russia, such as Russian war in Ukraine and the resulting international economic sanctions, had a much greater impact on the volatility of European stocks compared to the volatility of the S&P 500.

Table 6: Averaged Joint Connectedness Table for EVT-VaR Sovereign CDS Data of BRICS and MIST Countries with VIX and VSTOXX Indices

	Brazil	China	India	Indonesia	Korea	Mexico	Russia	South Africa	Turkey	VIX	VSTOXX	FROM
Brazil	31.99	6.29	3.77	6.86	5.93	18.99	7.65	7.19	3.93	4.71	2.66	68.01
China	7.60	17.58	7.58	13.87	12.38	11.82	11.19	6.92	3.94	4.06	3.06	82.42
India	4.88	8.20	40.06	7.29	3.52	9.09	15.53	3.64	3.14	1.98	2.66	59.94
Indonesia	9.91	13.67	6.17	18.13	11.51	13.40	9.39	7.38	4.15	4.03	2.24	81.87
Korea	6.93	14.38	3.96	14.15	24.66	8.36	9.56	5.65	3.30	5.47	3.60	75.34
Mexico	16.22	8.00	4.91	7.65	5.25	23.66	12.16	8.00	5.03	5.53	3.58	76.34
Russia	3.80	3.83	6.89	2.99	1.66	7.73	65.92	3.20	2.23	1.02	0.73	34.08
South Africa	9.63	6.12	3.65	7.14	4.75	12.64	10.41	33.21	8.02	2.32	2.12	66.79
Turkey	5.86	5.03	3.09	5.65	3.20	8.18	7.08	8.66	49.74	1.57	1.94	50.26
VIX	3.94	2.14	2.35	3.02	2.16	4.66	4.87	2.15	1.30	57.95	15.47	42.05
VSTOXX	2.63	3.65	3.28	3.01	3.28	4.04	11.78	3.53	2.11	22.37	40.33	59.67
TO	71.40	71.31	45.66	71.63	53.64	98.91	99.61	56.31	37.15	53.06	38.07	696.76
Inc.Own	103.40	88.89	85.73	89.76	78.31	122.57	165.53	89.52	86.89	111.01	78.40	TCI
NET	3.40	-11.11	-14.27	-10.24	-21.69	22.57	65.53	-10.48	-13.11	11.01	-21.60	63.34
NPT	6.00	4.00	4.00	5.00	0.00	8.00	10.00	5.00	3.00	8.00	2.00	

The energy crisis caused by the Russia-Ukraine war is shaking the economy like the great energy crisis in the 1970s. According to the OECD Economic Outlook (OECD, 2022a), it is estimated that global growth will decrease to 2.2 percent in 2023 and will be 2.7 percent in 2024. Although the growth rate slowed down because of the pandemic, high inflation caused by the Russia-Ukraine war and the increase in energy and food prices make the situation of countries difficult. Countries have increased their interest rate levels to control inflation and stabilize the inflation expectations in their economies. Many measures have been taken to alleviate the economic distress caused by high energy and food prices. However, since energy prices are likely to remain high and volatile for a while, it is important for countries to implement measures to encourage energy savings.

According to the World Energy Outlook (IEA, 2022), if the effects of the global energy crisis caused by the Russia-Ukraine War continue in the coming years, access to electricity for 70 million people will be interrupted soon because it is not affordable. Continuing to use fossil fuels and Russia's position as the primary exporter are the main factors of the energy crisis and it is necessary to turn to clean energy policies. Clean energy is a great opportunity for growth and employment and is important for international economic competitiveness. For example, the US Inflation Reduction Act aims to increase annual solar and wind capacity additions in the US two-and-a-half times today's levels and increase electric car sales sevenfold by 2030 (IEA, 2022). The US Inflation Reduction Act encourages the use of alternative fuels instead of natural gas and other fossil fuels and applies regional subsidies to compensate for their losses to places whose economy formerly depended on fossil fuels (US Inflation Reduction Act, 2022).

European countries are most affected by the extreme shocks originating from Russia due to energy dependency, and downside risks in energy markets continue. The energy crisis originating from Russia has brought with it the debates on long-term energy security. European countries had invested in natural gas storage facilities much earlier. Although Europe has enough storage to survive 2022-2023, it is possible to experience power outages in 2023-2024.

In recent years, countries have turned to renewable energy sources (hydro, geothermal, solar, wind, biomass, etc.) because the reserves of fossil resources such as natural gas are not sustainable. Although the production costs of some renewable resources such as solar and biomass have decreased, the production-investment unit costs are still at very high levels (IEA, 2022). Thus, policies for countries to pursue the transition to carbon neutrality help reduce dependency on fossil fuels but can only be successful when policies provide affordable access to low and zero carbon options. If prices continue to remain high, governments should continue to provide targeted support to financially vulnerable households. (OECD, 2022b)

Table 7: Averaged Joint Connectedness Table for Sovereign CDS Return Data of BRICS and MIST Countries with VIX and VSTOXX Indices

	Brazil	China	India	Indonesia	Korea	Mexico	Russia	South Africa	Turkey	VIX	VSTOXX	FROM
Brazil	32.02	4.19	1.70	4.96	3.99	19.60	6.94	10.46	6.71	5.56	3.86	67.98
China	7.00	21.29	4.88	17.75	15.49	8.04	4.93	6.86	4.20	5.08	4.48	78.71
India	3.35	5.74	63.10	7.92	5.41	4.11	2.71	2.96	1.87	1.61	1.21	36.90
Indonesia	8.47	15.39	5.64	18.15	13.02	9.63	6.13	8.31	5.61	5.33	4.31	81.85
Korea	6.27	15.76	4.41	15.07	26.94	7.47	4.69	6.11	4.03	5.09	4.16	73.06
Mexico	18.85	4.42	2.05	5.43	4.57	28.25	7.74	10.99	6.90	6.29	4.51	71.75
Russia	6.80	3.01	1.49	4.35	3.04	7.77	50.32	10.04	7.46	2.42	3.28	49.68
South Africa	10.04	4.80	1.74	6.50	4.38	10.80	9.73	29.78	12.93	4.01	5.30	70.22
Turkey	7.44	3.46	1.27	4.68	3.18	7.69	7.94	14.14	43.06	3.01	4.12	56.94
VIX	6.81	1.90	0.74	2.43	1.99	8.01	2.83	5.19	3.32	53.45	13.35	46.55
VSTOXX	4.74	3.17	0.77	3.50	2.97	5.70	4.30	6.84	4.79	13.96	49.25	50.75
TO	79.77	61.84	24.67	72.58	58.03	88.82	57.96	81.90	57.83	52.37	48.60	684.37
Inc.Own	111.80	83.13	87.78	90.73	84.97	117.08	108.28	111.68	100.89	105.82	97.84	TCI
NET	11.80	-16.87	-12.22	-9.27	-15.03	17.08	8.28	11.68	0.89	5.82	-2.16	62.22
NPT	7.00	2.00	0.00	3.00	1.00	9.00	8.00	10.00	6.00	5.00	4.00	

Figure 18: Averaged Dynamic Total Connectedness of BRICS and MIST Countries with VIX and VSTOXX Indices

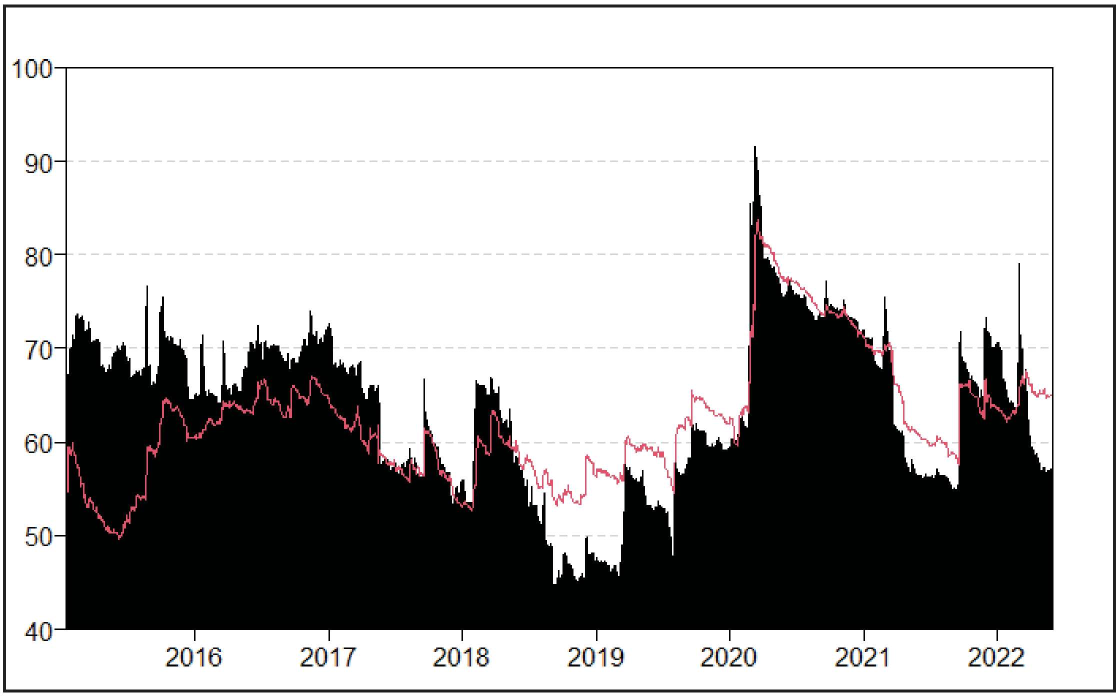


Figure 19: Net Dynamic Total Connectedness of BRICS and MIST Countries with VIX and VSTOXX Indices

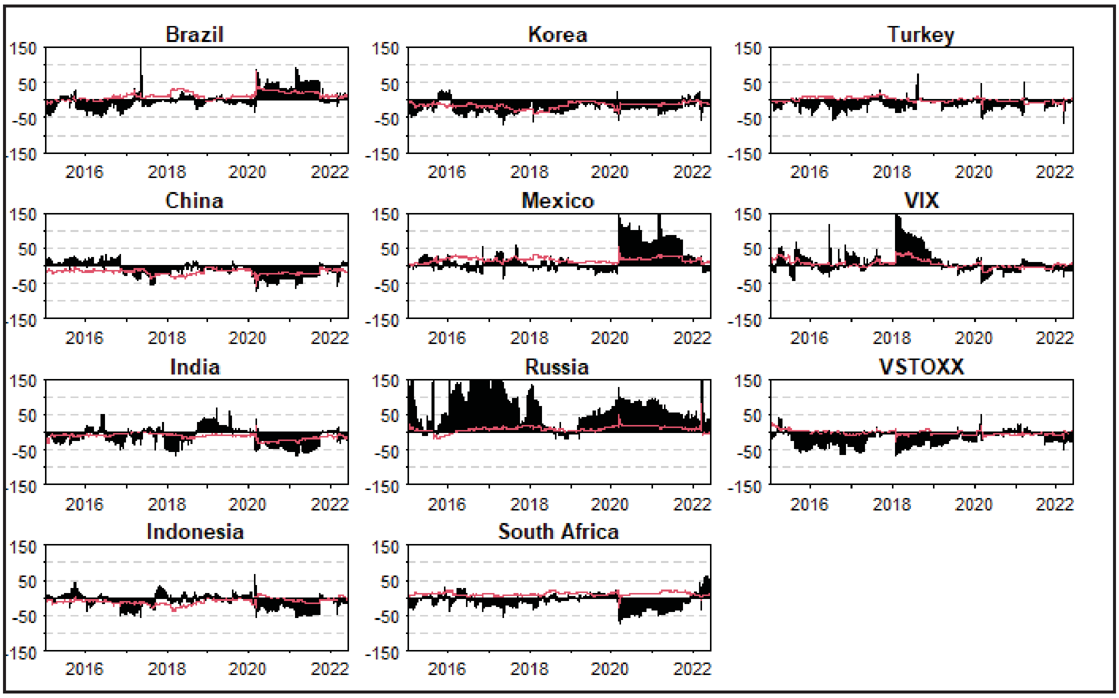
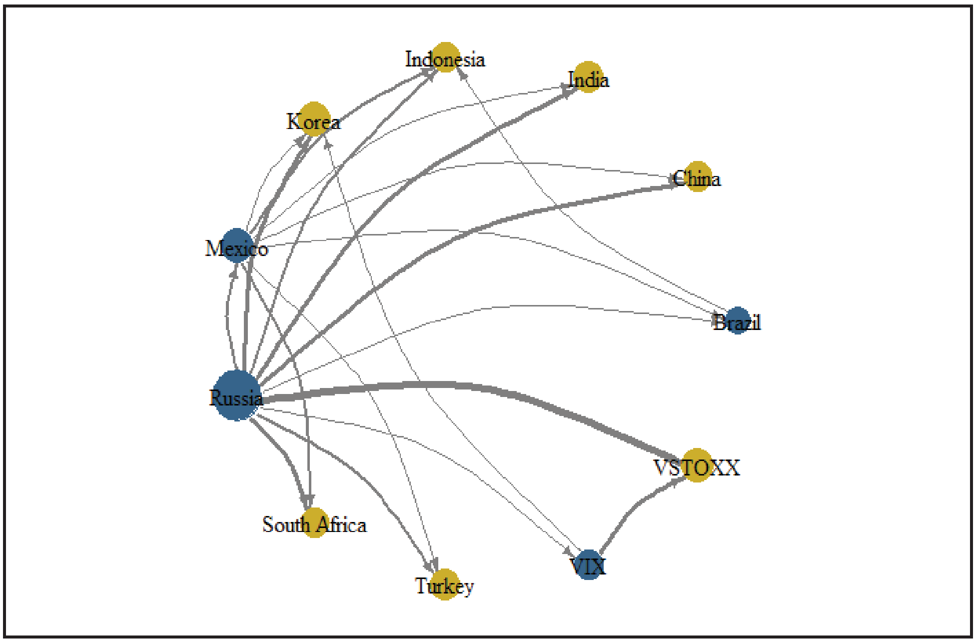
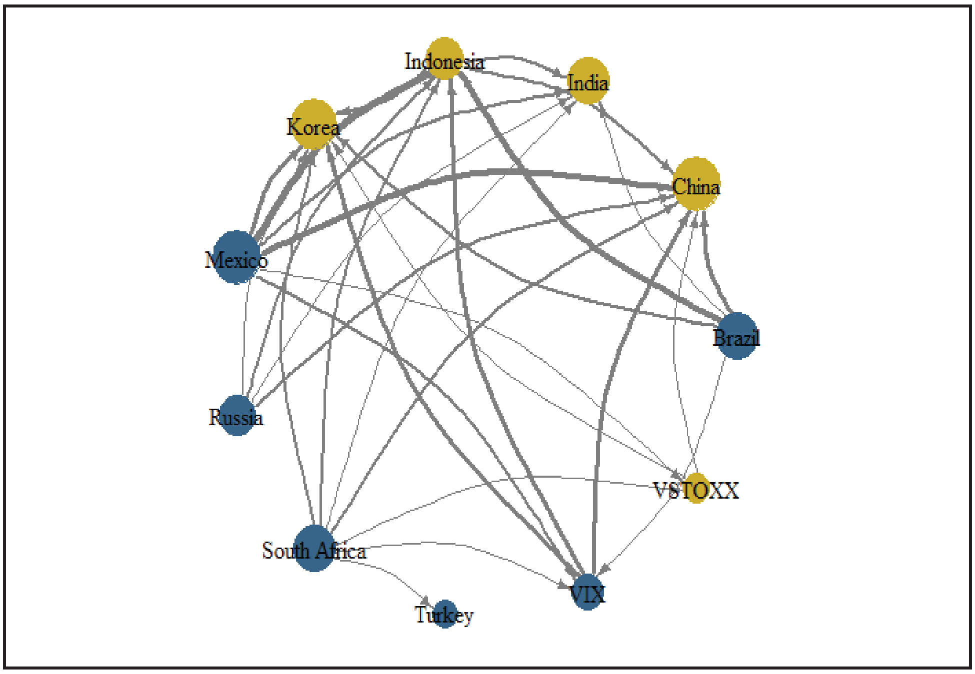


Figure 20: Dynamic Net Pairwise Connectedness Plots for EVT-VaR and Return Series of BRICS and MIST Countries with VIX and VSTOXX Indices





3.7 PRINCIPAL COMPONENT ANALYSIS

In this section, using the Principal Component Analysis (PCA), an extreme connectedness analysis was carried out for sovereign CDSs covering many countries around the world. In this section, the extended joint connectedness analysis is estimated with both 2 lags, which is the optimal lag number selected according to the SC criteria, and 14 lag, which is the optimum lag number according to the AIC (Akaike's information criterion**)** and FPE (final prediction error) criteria, to show the effect of the lag number on the analysis. As a result, it was found that the analysis is robust to the number of lags.

Firstly, EVT-VaR values were calculated for sovereign CDS series of all countries by applying the dynamic extreme value theorem. Then, all countries other than the BRICS and MIST countries were grouped according to their EU membership and geographic location, and then common factors were identified for each group through the PCA analysis. We included the United States and the United Kingdom separately in the analysis. We estimated principal components for BRICS and MIST countries and the rest of the countries are grouped based on geographical location. In conclusion, we analyzed the extreme risk connectedness of 41 countries. Within the scope of this thesis, a considerable number of national figures were included in the analysis, but the number of figures was reduced by performing the principal component analysis before the connectedness study.

The countries within the scope of each country group and the details of the PCA analysis regarding them are given below. After finding the principal component of each county groups, we analyzed the contribution of the countries to each principal component.

3.7.1 BRICS Countries

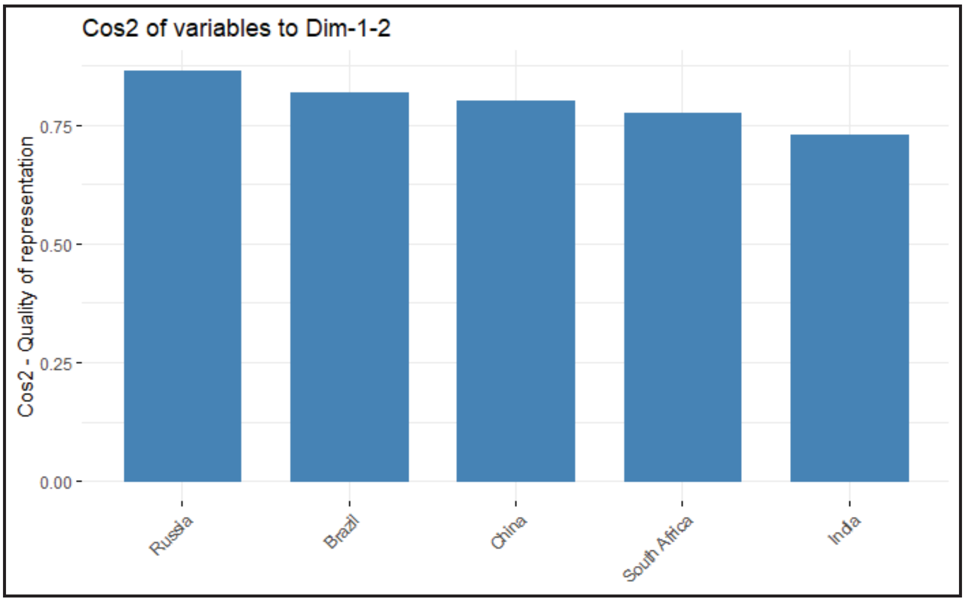
BRICS Countries, namely Brazil, Russia, India, China, and South Africa were grouped using the PCA. Table 8 demonstrates that the 59% of the variation in BRICS Countries Sovereign CDS dataset can be attributed to the first principal components.

Figure 21 illustrates that Russia and Brazil are the countries which contribute to the principal components most in the BRICS group.

Table 8: Importance of Components for BRICS Countries

	Importance of Components				
	PC1	PC2	PC3	PC4	PC5
Standard deviation	1.7221	1.0104	0.65797	0.56361	0.51279
Proportion of Variance	0.5931	0.2042	0.08659	0.06353	0.05259
Cumulative Proportion	0.5931	0.7973	0.88388	0.94741	1

Figure 21: Contribution of Countries to PCA Components for BRICS Countries



3.7.2 MIST Countries

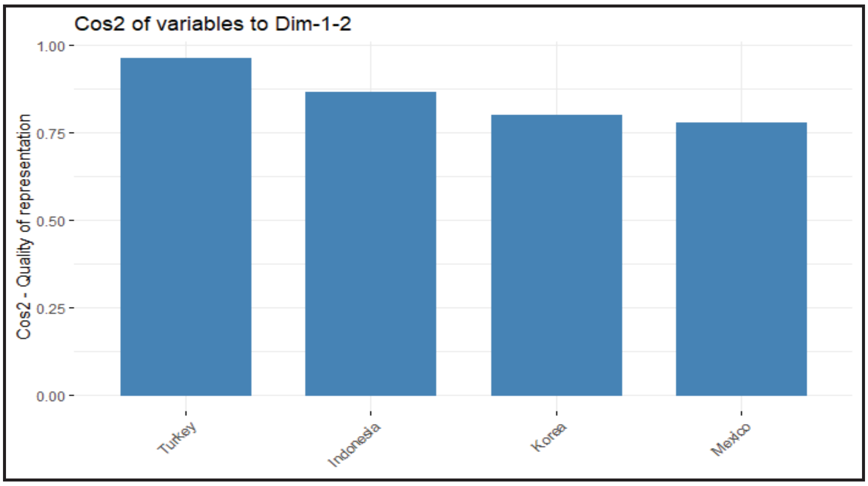
MIST Countries, namely Mexico, Indonesia, South Korea, and Türkiye are grouped using the PCA. Table 9 demonstrates that approximately 69% of the variation in MIST countries sovereign CDS dataset can be attributed to the first principal components.

The Figure 22 shows that Türkiye and Indonesia are the countries which contribute to the principal components most in the MIST group.

Table 9: Important of Components for MIST Countries

	Importance of Components			
	PC1	PC2	PC3	PC4
Standard deviation	1.6578	0.8087	6386	0.4357
Proportion of Variance	0.6871	0.1635	0.1019	0.04746
Cumulative Proportion	0.6871	0.8506	0.9525	1

Figure 22: Contribution of Countries to PCA Components for MIST Countries



3.7.3 European Union Countries

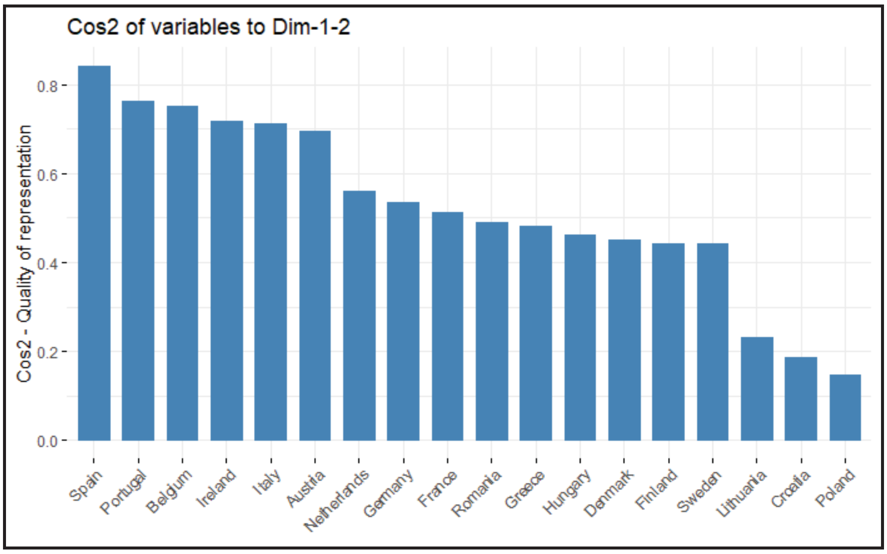
EU Countries, namely Austria, Belgium, Croatia, Denmark, Greece, Finland, France, Germany, Hungary, Ireland, Italy, Lithuania, Netherlands, Poland, Portugal, Romania, Spain, and Sweden were grouped using the PCA. Table 10 demonstrates that approximately 40% of the variation in EU Countries Sovereign CDS dataset can be attributed to the first principal components.

Figure 23 shows Spain, Portugal, and Belgium are the countries which contribute to the principal components most in the EU Countries.

Table 10: Importance of Components for EU Countries

	Importance of first k=10 (out of 18) Components									
	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10
Standard deviation	2.6771	1.5021	1.19121	1.05937	0.95584	0.89133	0.81364	0.79694	0.74033	0.71207
Proportion of Variance	0.3982	0.1253	0.07883	0.06235	0.05076	0.04414	0.03678	0.03528	0.03045	0.02817
Cumulative Proportion	0.3982	0.5235	0.60236	0.66471	0.71547	0.7596	0.79638	0.83167	0.86211	0.89028

Figure 23: Contribution of Countries to PCA Components for EU Countries



3.7.4 Asian Countries

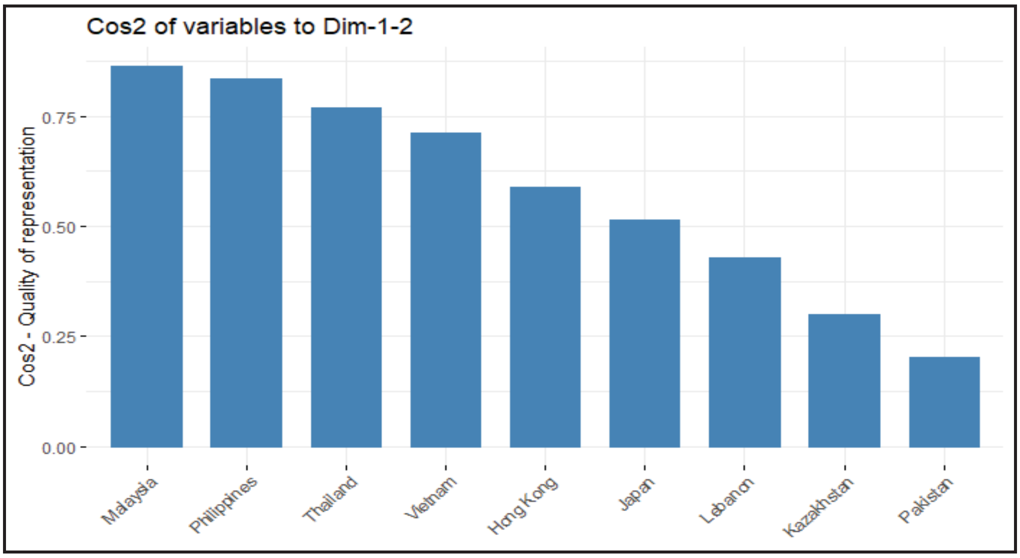
Asian countries, namely Malaysia, Philippines, Thailand, Vietnam, Kazakhstan, Hong Kong, Pakistan, Lebanon, and Japan, were grouped using the PCA. Table 11 demonstrates that approximately 43% of variation in Asian countries sovereign CDS dataset can be attributed to the first principal components.

Figure 24 shows Malaysia, Philippines, and Thailand, which are the countries contributing to the principal component most in the Asian countries.

Table 11: Importance of Components for Asian Countries

	Importance of Components								
	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9
Standard deviation	1.9693	1.1546	1.0489	0.88816	0.8674	0.69928	0.58381	0.46405	0.31918
Proportion of Variance	0.4309	0.1481	0.1222	0.08765	0.0836	0.05433	0.03787	0.02393	0.01132
Cumulative Proportion	0.4309	0.579	0.7013	0.78895	0.8726	0.92688	0.96475	0.98868	1

Figure 24: Contribution of Countries to PCA Components for Asian Countries



3.7.5 Latin American Countries

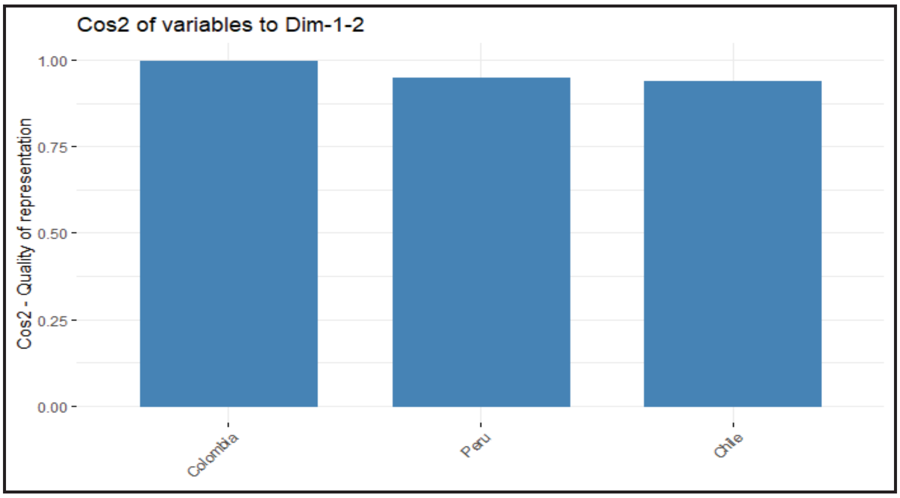
Latin American countries, namely Chile, Colombia, and Peru, were grouped using the PCA. Table 12 demonstrates that approximately 90% percent of the variation in Latin American countries sovereign CDS dataset can be attributed to the first principal components.

Figure 25 indicates that Columbia and Peru are the countries which contribute to the principal components most in the Latin American countries.

Table 12: Importance of Components for Latin American Countries

	Importance of Components		
	PC1	PC2	PC3
Standard deviation	1.6482	0.41593	0.33232
Proportion of Variance	0.9055	0.05767	0.03681
Cumulative Proportion	0.9055	0.96319	1

Figure 25: Contribution of Countries to PCA Components for Latin American Countries



3.7.6 Empirical Results of the EVT-VaR Extended Joint Connectedness Analysis with PCA

When Table 13 is examined, averaged total connectedness value of the country groups is 64.01, which is quite high. While BRICS and EU countries are net shock transmitters, all other countries are net shock receivers. If we review Figures 27 and 28, it is seen that the spillover effect from EU countries to the United Kingdom is very high. Especially after the 2016 United Kingdom's European Union membership referendum, changes in the sovereign CDS EVT-VaR values of EU countries spread rapidly to the United Kingdom due to uncertainty about the future of the European Union after the Brexit referendum.

When the dynamic total connectedness in Figure 26 is investigated, it is seen that the extreme risk connectedness, which covers the EVT-VaR CDS return values of all countries, has changed significantly over time. The extreme risk connectedness is unprecedentedly high after the Covid 19 pandemic as of the analysis period, and it continues in this way because of the Russian war in Ukraine and the food and energy crises that followed.

The rapid rise in healthcare expenditures and social benefits due to Covid 19, the recent energy and food crisis, and the devaluation of emerging country currencies against the US dollar have brought along risks regarding many emerging markets' financial stability and repayment of foreign debts. In the recent period, the sustainability of the financial structure of the countries and the threat of debt crises represent one of the most important issues.

In Figure 28, it is seen that the United States has very limited interaction with other countries. The United States sovereign CDS values are quite low, and it is seen that they are not affected by extreme events that occur in other countries. The only exception to this is that it was partially affected by the EU and Asia after 2018.

Table 13: Averaged Joint Connectedness Table for EVT-VaR Sovereign CDS Data with PCA (with 2 lag)

	United Kingdom	**United States**	**pc1_eu**	**pc1_asia**	**pc1_latin**	**pc1_brics**	**pc1_mist**	**FROM**
United Kingdom	49.03	2.22	23.08	7.93	6.37	4.40	6.98	50.97
United States	2.85	76.46	5.88	4.99	3.11	3.20	3.51	23.54
pc1_eu	10.93	3.88	42.11	13.04	9.86	9.67	10.50	57.89
pc1_asia	4.09	4.05	14.86	14.87	15.61	22.06	24.46	85.13
pc1_latin	4.30	2.83	13.09	14.55	25.34	20.35	19.54	74.66
pc1_brics	2.54	2.58	10.41	17.43	17.28	29.78	19.98	70.22
pc1_mist	4.26	2.31	13.35	22.10	19.02	24.63	14.34	85.66
TO	28.97	17.88	80.66	80.04	71.25	84.31	84.96	448.07
Inc.Own	78.00	94.33	122.77	94.91	96.58	114.09	99.31	TCI
NET	-22.00	-5.67	22.77	-5.09	-3.42	14.09	-0.69	64.01
NPT	1.00	0.00	6.00	2.00	3.00	5.00	4.00	

Table 14: Averaged Joint Connectedness Table for EVT-VaR Sovereign CDS Data with PCA (with 14 lag)

	United Kingdom	United States	pc1_eu	pc1_asia	pc1_latin	pc1_brics	pc1_mist	FROM
United Kingdom	54.57	3.94	18.70	6.26	5.83	4.14	6.57	45.43
United States	2.56	74.78	4.12	5.24	4.76	3.36	5.18	25.22
pc1_eu	11.12	3.50	43.26	11.45	10.93	8.14	11.60	56.74
pc1_asia	3.98	4.03	13.06	18.32	15.33	20.11	25.17	81.68
pc1_latin	4.11	3.41	12.11	12.33	29.91	19.28	18.83	70.09
pc1_brics	3.08	2.67	10.17	16.68	18.05	28.47	20.88	71.53
pc1_mist	4.07	3.31	11.73	20.24	20.20	23.08	17.38	82.62
TO	28.92	20.87	69.89	72.19	75.10	78.11	88.23	433.31
Inc.Own	83.50	95.64	113.15	90.51	105.01	106.57	105.61	TCI
NET	-16.50	-4.36	13.15	-9.49	5.01	6.57	5.61	61.90
NPT	0.00	1.00	6.00	2.00	4.00	5.00	3.00	

Figure 26: Averaged Dynamic Total Connectedness of BRICS and MIST Countries with PCA

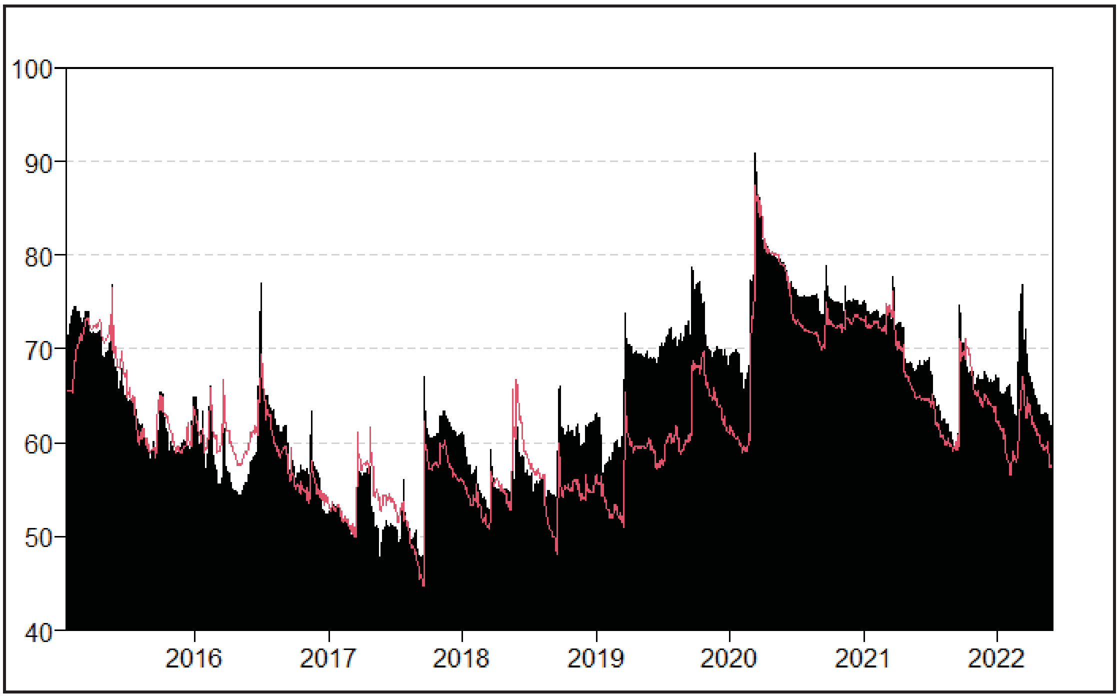


Figure 27: Net Dynamic Total Connectedness of BRICS and MIST Countries with PCA

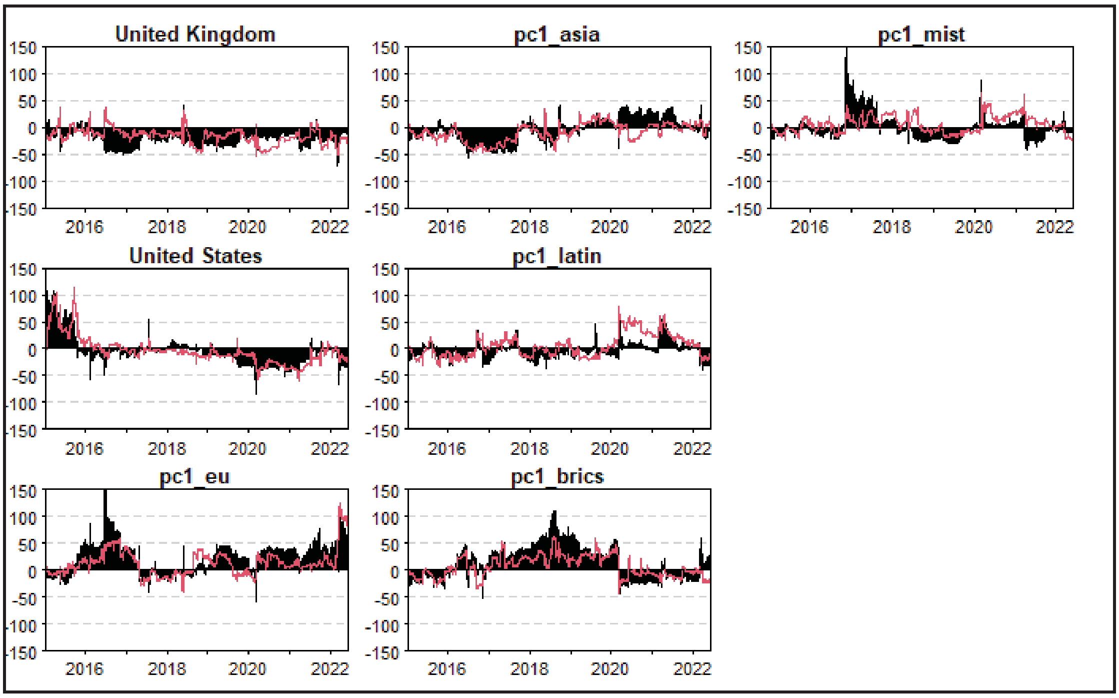
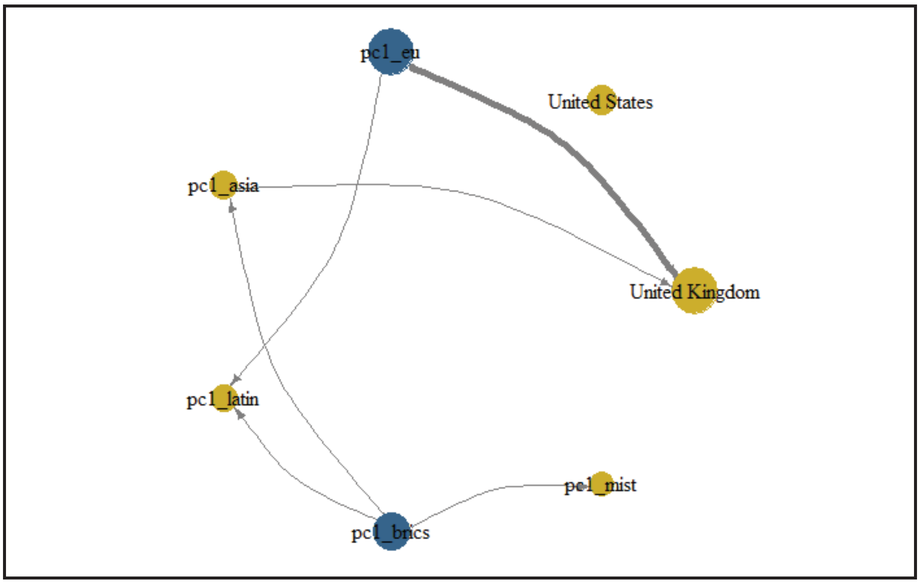
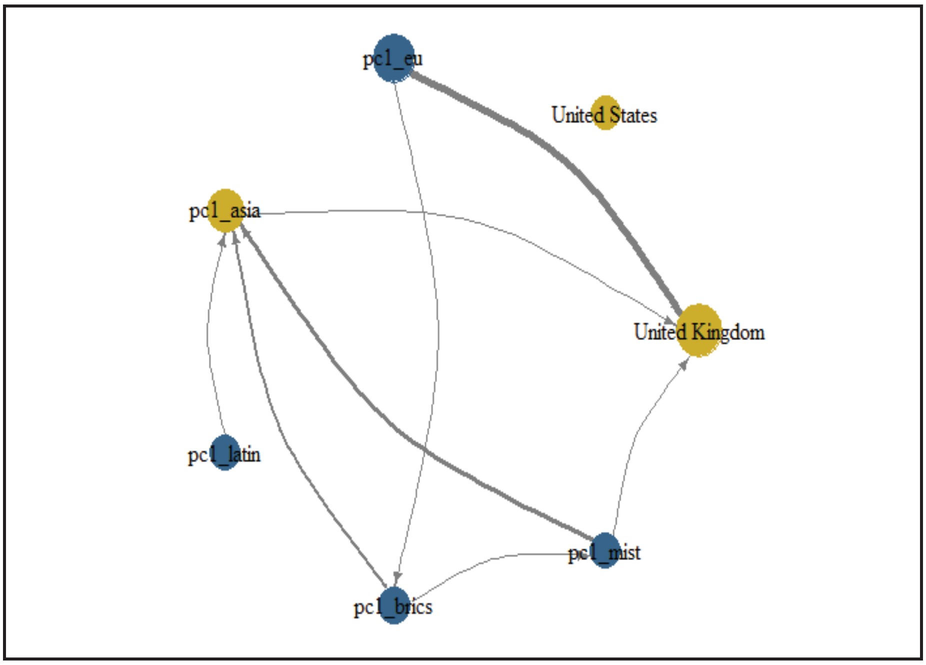


Figure 28: Dynamic Net Pairwise Connectedness Plots for EVT-VaR and Return Series of BRICS and MIST Countries with PCA





3.8 COMPARISON OF EVT-VAR EXTENDED JOINT CONNECTEDNESS ANALYSIS AND QUANTILE EXTENDED JOINT CONNECTEDNESS ANALYSIS

“The Quantile Extended Joint Connectedness Approach” developed by Cunado, J et al. (2022) and the dynamic EVT-VaR connectedness approach proposed by this thesis were compared using the sovereign CDS data. The connectedness results calculated based on “The Quantile Extended Joint Connectedness Approach” for BRICS and MIST countries are given in Table 15. In Table 15, “The Quantile Extended Joint Connectedness Approach” is calculated for 1% percentile. The total extreme risk connectedness value is very high with 92.89, indicating that the extreme risks are closely interrelated in the network consisting of BRICS and MIST countries.

When the total connectedness calculated with quantile extended joint connectedness using sovereign CDS return values (Table 15) is compared with the connectedness values calculated with dynamic EVT-VaR connectedness approach (Table 2), the quantile extended joint connectedness values are quite high. However, the quantile extended joint connectedness approach does not respond as sensitively as dynamic EVT-VaR connectedness framework to extreme events that have occurred over time as seen in Figure 29. In addition, when Figures 30 and 31 are assessed, Russia's leading role in the extreme risk spillover becomes evident, although the net connectedness values are quite small for all countries.

Table 15: Averaged Joint Connectedness Table for EVT-VaR Sovereign CDS Data of BRICS and MIST Countries with Quantile Extended Joint Connectedness Analysis

	Brazil	**China**	**India**	**Indonesia**	**Korea**	**Mexico**	**Russia**	**South Africa**	**Turkey**	**FROM**
Brazil	5.87	11.38	10.69	11.60	11.20	13.31	12.11	12.04	11.80	94.13
China	11.62	5.61	11.10	12.75	12.69	11.75	11.44	11.56	11.48	94.39
India	10.76	11.00	12.06	11.32	11.07	11.04	11.02	10.91	10.81	87.94
Indonesia	11.81	12.33	11.09	6.00	12.17	11.97	11.59	11.68	11.35	94.00
Korea	11.44	12.79	11.06	12.67	6.52	11.62	11.33	11.40	11.15	93.48
Mexico	13.15	11.51	11.07	11.68	11.33	5.01	12.25	12.15	11.84	94.99
Russia	11.61	10.96	10.65	11.07	10.80	11.95	9.29	11.89	11.79	90.71
South Africa	12.02	11.14	10.90	11.48	11.11	12.31	12.04	6.60	12.41	93.40
Turkey	11.94	11.25	10.81	11.29	11.10	12.14	12.00	12.44	7.02	92.98
TO	94.36	92.38	87.38	93.85	91.48	96.09	93.78	94.08	92.62	836.03
Inc.Own	100.23	97.99	99.43	99.85	98.00	101.10	103.07	100.68	99.64	TCI
NET	0.23	-2.01	-0.57	-0.15	-2.00	1.10	3.07	0.68	-0.36	92.89
NPT	5.00	1.00	2.00	3.00	1.00	6.00	8.00	6.00	4.00	

Figure 29: Averaged Dynamic Total Connectedness of BRICS and MIST Countries with Quantile Extended Joint Connectedness Analysis

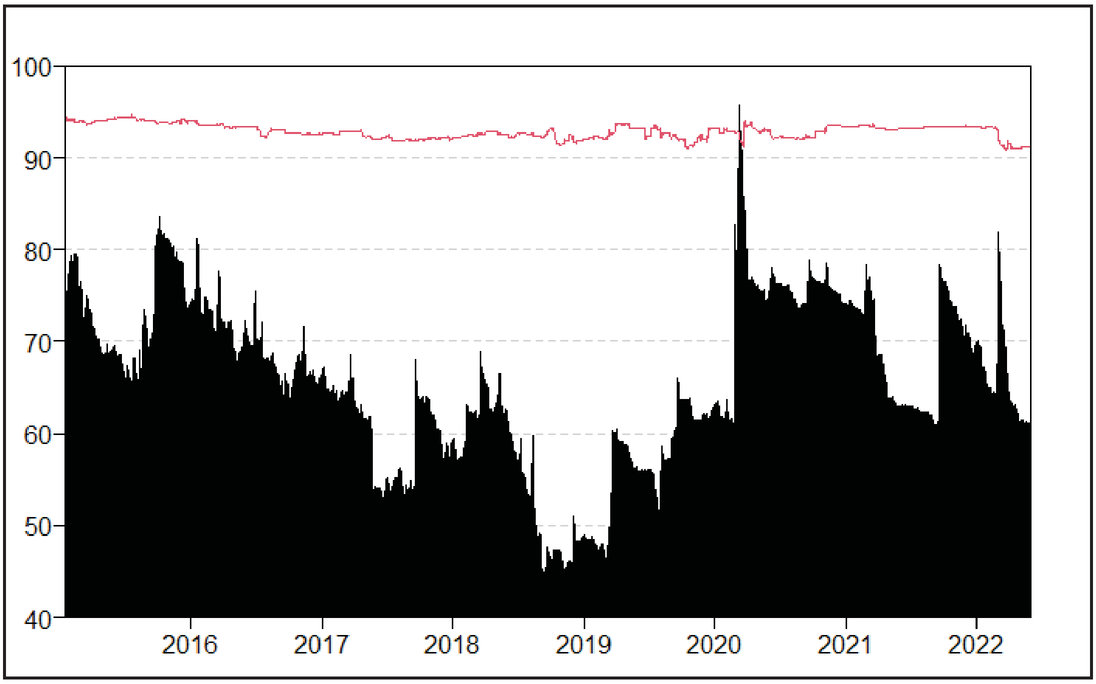


Figure 30: Net Dynamic Total Connectedness of BRICS and MIST Countries with Quantile Extended Joint Connectedness Analysis

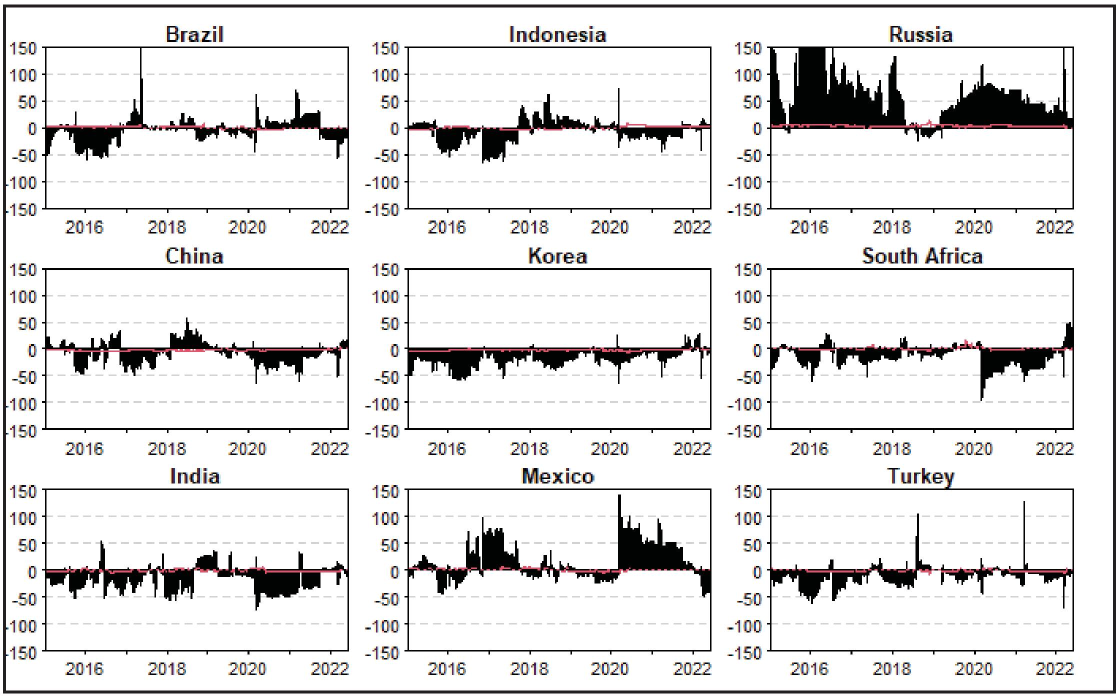
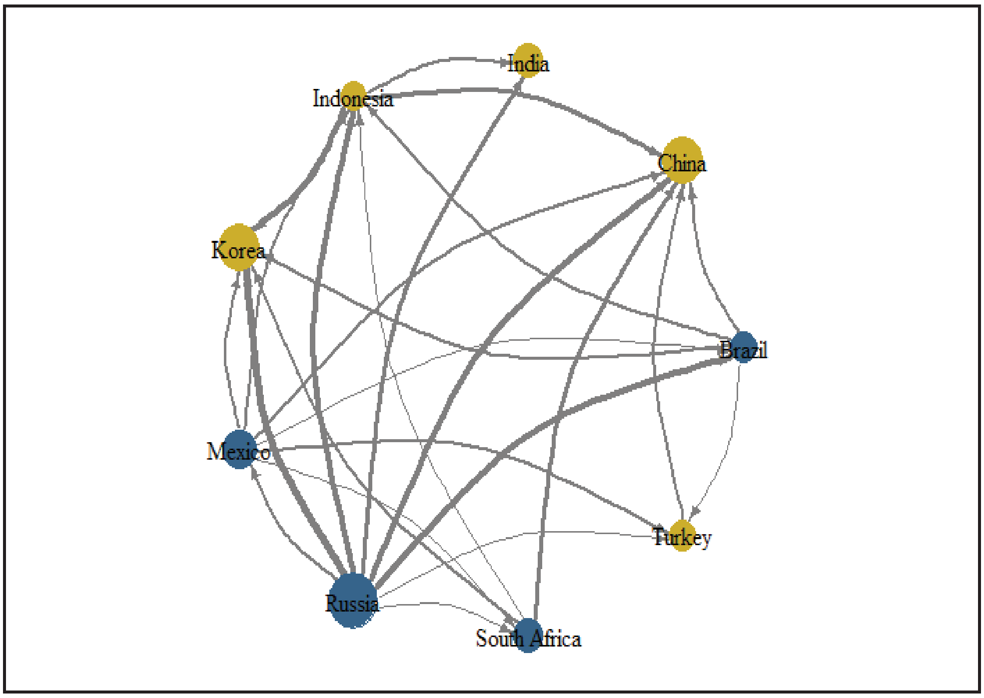


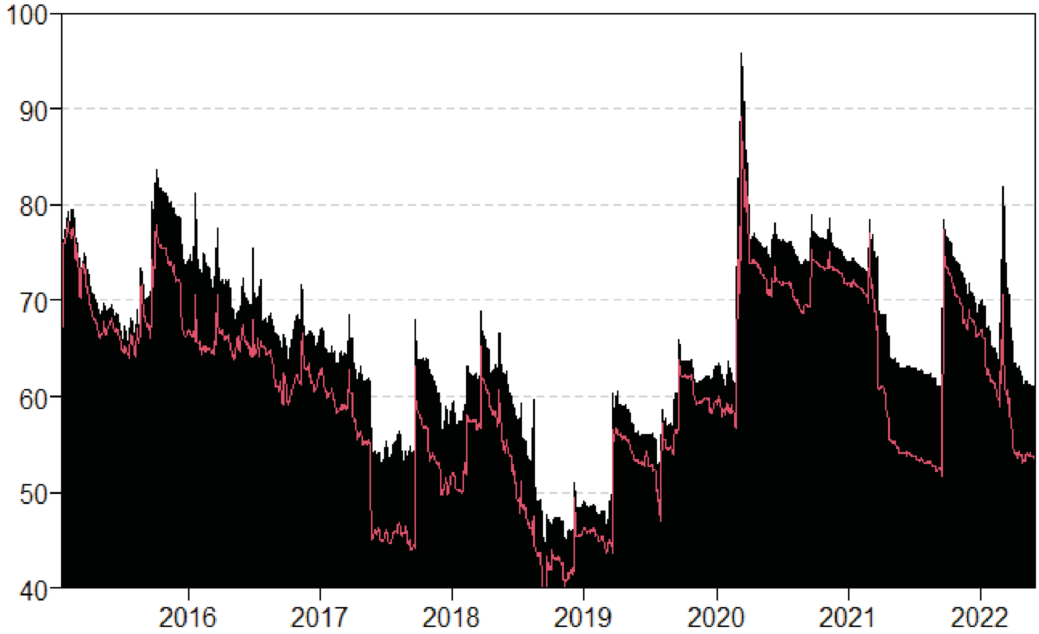
Figure 31: Dynamic Net Pairwise Connectedness Plots for EVT-VaR and Return Series of BRICS and MIST Countries with Quantile Extended Joint Connectedness Analysis



3.9 ROBUSTNESS ANALYSIS

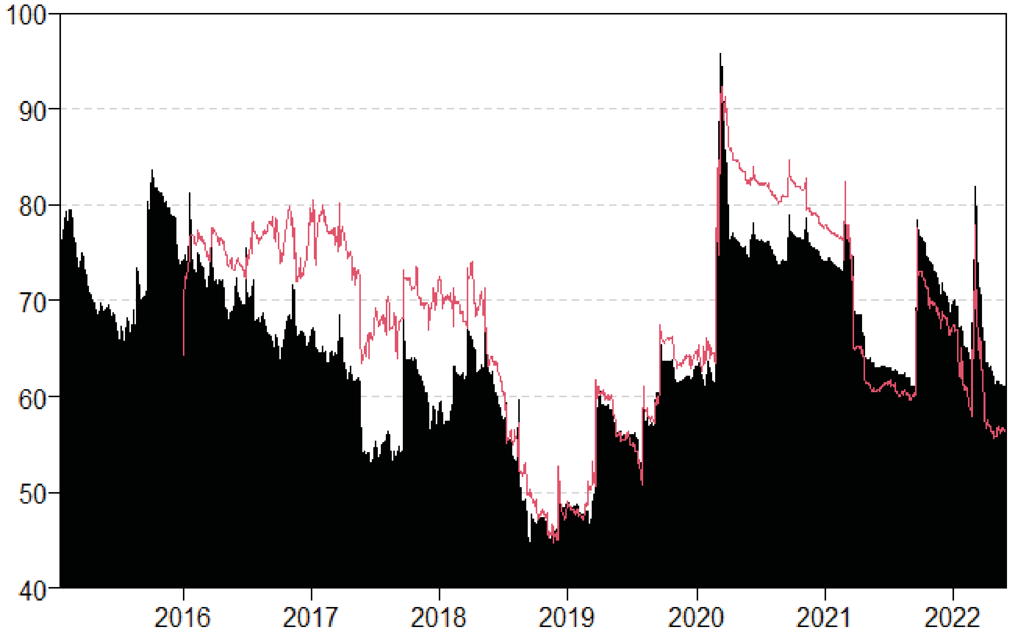
The EVT-VaR connectedness method used in the study of examining extreme risk spillovers of Credit Default Swaps depends on many parameters. The sensitivity of the model results to the most important tuning parameters will be discussed in this last section as an example. First, in the calculation of the EVT-VaR measure, forecasting time horizon is selected as 20 days. Figure 32 show the total connectedness result for 10 days forecast time horizon.

Figure 32 : Averaged Dynamic Total Connectedness of BRICS and MIST Countries with time horizon of 10 days.



the window size is determined as 1000 days. Since only a small fraction of the data are used while conducting prediction by the extreme value theorem, the model does not work when the window size is set too small. In contrast, if the window size is too large, the data loss rate increases excessively. In Figure 33 below, the estimated connectedness values in the cases of window sizes 1250 days are included. As you can see, the window size increases in the model averaged total connectedness mostly rises but the fundamental results of the model do not change, so the model is robust against the change in the window sizes.

Figure 33: Averaged Dynamic Total Connectedness of BRICS and MIST Countries with Window Size of 1250 Says in the EVT VaR Calculations.



CONCLUSION

Financial crises that occur in one country spread to other countries at a much higher rate because of financial integration. In particular, the 2007-2008 global financial crisis had a devastating effect on the financial markets of many countries due to the unprecedented spillover effect. For this reason, studies on risk calculation and the spillover methods have increased. In this context, although extreme events occur rarely, as the great crises show, their effects are very destructive. It is relatively difficult to calculate and predict extreme events because extreme risks occur rarely and thus the data on them are limited.

In this study, the dynamic EVT-VaR method was used to calculate extreme risks. In the literature, it has been proven via the backtesting method that the EVT-VaR method performs better than other methods in calculating extreme risks. The dynamic EVT-VaR method, which is a semi-parametric method, has many advantages over other methods. The variance covariance approach, which is widely used in calculating VaR, is a parametric model and assumes normal distribution, but this approach leads to an underestimation of the current risk, especially in the fat-tailed financial data. Non-parametric methods, such as the Monte Carlo simulation and the historical simulation approach, do not assume an underlying empirical distribution, but because they are nonparametric in nature, it is difficult to interpret, and their performance is poor in forward prediction. Due to the advantages mentioned above, extreme risks were calculated in this study using the dynamic EVT-VaR method.

Connectedness analysis is widely used in examining spillover effects in financial markets. Diebold and Yılmaz (2009, 2012, 2014) proposed the connectedness method by combining VAR variance-decomposition and network analysis. Connectedness analysis is a comprehensive tool enabling the multivariate analysis of the spillover effects and it also includes the directions of these spillover effects.

Many researchers have proposed new models to improve the DY connectedness approach. With the frequency connectedness method developed by Barunik and Krehlik (2015), the ordering problem was resolved, and at the same time, it allowed to decompose the short, medium, and long-term effects of shocks.

The Time Varying Connectedness method developed by Antonakakis and Gabauer (2017) allowed the calculation of dynamic connectedness without using the rolling window. The most important advantage of the TVP-VAR method compared to the rolling window method is that there is no need to choose a random window size. It avoids also losing data as large as the window size. In addition, the TVP-VAR approach is less sensitive to the effects of outliers.

The Joint Spillover Index approach, which was proposed by Lastrapes and Wiesen (2020) as an alternative method for measuring connectedness, also developed a more robust method by considering the effects of correlation between the contributing variables. “The TVP-VAR Extended Joint Connectedness Approach” was suggested by Balcilar et al. (2020) to overcome the main problem of this system, which is related to the calculation of the net directional connectedness value. “TVP-VAR Extended Joint Connectedness Approach” proposed by Balcilar et al. (2020) was used in this study.

To analyze the extreme risk spillover effect, this thesis proposes the dynamic EVT-VaR extended joint connectedness framework based on the Extreme Value Theory, and the spillovers between sovereign CDS of BRICS and MIST countries using the data from March 18, 2011 to June 1,2022 were examined. It is seen that there is a strong spillover effect among the sovereign CDSs of the countries in the BRICS and MIST, and this spillover effect has fluctuated over time due to extreme events. Among these countries, Russia has a pronounced role as a net transmitter of shock. After Russia, Mexico has been one of the important drivers in explaining the variability in sovereign CDS spreads in BRICS and MIST countries, especially in 2017-2018 and after 2020.

In addition, global financial factors were included in the model and their effects were analyzed. Global financial factors have a limited impact on sovereign CDSs in the BRICS and MIST countries. Besides, using the Principal Component Analysis (PCA), an extreme connectedness analysis was executed for sovereign CDSs of many leading countries around the world. Using the PCA analysis we found out that there is an unprecedented increase in the total connectedness value of sovereign CDS around the world after the Covid 19 pandemic and the connectedness value continues to remain high at present time.

Another finding of the study is that Türkiye is not strongly interconnected with other economies. Türkiye, which was only affected by a shock in South Africa sovereign CDS to a limited extent as a shock recipient, stands apart from other countries. As a result of limited interconnectedness, Türkiye was affected less by systematic risks. On the other hand, Türkiye has a high level and volatile sovereign CDS values, which means that the country's high-risk perception stems from events occurring within the country itself, rather than external factors.

Finally, the dynamic EVT-VaR extended joint connectedness framework and the quantile extended joint connectedness approach were compared using the sovereign CDSs of BRICS and MIST countries. The quantile extended joint connectedness approach does not respond as sensitively as the EVT-VaR extended joint connectedness framework to extreme events occurring over time.

Studies analyzing the spillover effects among countries and sectors have increased considerably in recent years and the common result of these researches is that connectedness increase before and during the economic distress conditions. Since the connectedness has also increased even before the major crises, the surge in extreme risks should be monitored closely by investors and policymakers as an early warning mechanism and necessary measures should be taken to reduce the effects of these systemic risks. Likewise, each country should closely follow the countries with which they have strong linkages, and those where they are potentially exposed to extreme adverse risks from. Governments should take policy measures to reduce the effects of these spillover effects beforehand.

Although connectedness values generally surge before the crucial crises, majority of the extreme events can be caused by unpredictable events that do not directly depend on economic and financial outlook, such as the in the case of Covid-19 pandemic or the Ukrainian Russian war. However, the economic and financial fundamentals of the countries may be crucial in determining the degree of the effects of extreme events. For example, the COVID-19 pandemic has already had a greater impact on countries with unstable financial structures and high public debt ratios. Based on these explanations, the reason why each country responds to extreme events differently can be a research topic in the future.

Investigation of the reasons for the upsurge in connectedness, especially in extreme market conditions, will guide policymakers to take precautions against the impact of extreme movements in financial markets. For example, governments will need to reconsider their debt management strategies, as one of the reasons for the increase in connectedness for an emerging country may be the exposure of the high amounts of inflows and outflows of international fund investments. In addition, when common global risks are realized, all emerging markets are collectively affected from them because of the asset management behavior of investors. Even if governments have a strong economic infrastructure and indicators, an extreme international event will affect all countries together, so BRICS and MIST governments, which are among the leading emerging countries, should closely follow these common global factors.

The extreme risk connectedness method proposed in this study provides advantages to further studies and it is possible to extend the EVT-VaR connectedness approach in many aspects. Other connectedness methods except for extended joint connectedness, such as frequency and elastic net connectedness approaches can be used in the analysis of the spillover effects of the risk measure obtained using the EVT-VaR application. For example, in the cases where the number of variables is high, using the elastic net connectedness method might be more effective. It is also possible to apply this method to many markets such as equity, bond, oil, and precious metal markets.

In addition, the analysis of the determinants of extreme risk connectedness will also be an intriguing study subject. For example, using the method proposed in this study, it is possible to analyze how portfolio allocation decisions of asset managers for emerging countries increase the extreme risks spillovers in these countries. It will be also an important research topic how the energy dependency structure of the countries affects the extreme risk connectedness network.

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İKTİSAT ANABİLİM DALI BAŞKANLIĞI'NA

Tarih: 20/02/2023

Tez Başlığı: Extreme Risk Connectedness of Sovereign Credit Default Swaps: Evidence from BRICS and MIST Countries

Yukarıda başlığı gösterilen tez çalışmam:

1. İnsan ve hayvan üzerinde deney niteliği taşımamaktadır,
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3. Beden bütünlüğüne müdahale içermemektedir.
4. Gözlemsel ve betimsel araştırma (anket, mülakat, ölçek/skala çalışmaları, dosya taramaları, veri kaynakları taraması, sistem-model geliştirme çalışmaları) niteliğinde değildir.

Hacettepe Üniversitesi Etik Kurullar ve Komisyonlarının Yönergelerini inceledim ve bunlara göre tez çalışmamın yürütülebilmesi için herhangi bir Etik Kurul/Komisyon'dan izin alınmasına gerek olmadığını; aksi durumda doğabilecek her türlü hukuki sorumluluğu kabul ettiğimi ve yukarıda vermiş olduğum bilgilerin doğru olduğunu beyan ederim.

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ADVISER COMMENTS AND APPROVAL

APPROVED.

Assoc.Prof. Nasip BOLATOĞLU

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SOSYAL BİLİMLER ENSTİTÜSÜ
DOKTORA TEZ ÇALIŞMASI ORİJİNALLİK RAPORU

HACETTEPE ÜNİVERSİTESİ
SOSYAL BİLİMLER ENSTİTÜSÜ
İKTİSAT ANABİLİM DALI BAŞKANLIĞI'NA

Tarih: 22/02/2023

Tez Başlığı : Extreme Risk Connectedness of Sovereign Credit Default Swaps: Evidence from BRICS and MIST Countries

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